Examining Reading Growth Profiles among Children of Diverse Language Backgrounds Using the Early Childhood Longitudinal Study (1999-2008): Multiple-Group Latent Curve and Growth Mixture Analyses

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Abstract

Previous research examining the reading achievement of immigrant children has often grouped English learners into one broad category, referred to as ELs, thereby creating an “either-or” dichotomy regarding whether or not these students need school language supports. The present study examined the theoretical contention regarding the “heterogeneity” existing among language minority children’s reading achievement growth spanning from kindergarten through grade eight utilizing a nationally representative longitudinal dataset, the Early Childhood Longitudinal Study—Kindergarten, 1999-2008. The goal of the study was threefold: (1) to identify the model of best utility in describing the longitudinal reading growth trends across children with diverse linguistic backgrounds [i.e., English Monolinguals, English Bilinguals, Mixed Bilinguals, and LEP (Limited English Proficient)]; (2) to examine the mechanisms underlying language minority students’ reading development vis-à-vis their English monolingual counterparts with respect to family socioeconomic status, home literacy practices, classroom literacy instruction and ESL programs; and (3) to investigate the indirect role of school contexts and processes on student reading growth through mediating latent reading profile groups using growth mixture modeling (GMM). The research sought to advance the study of language minority students’ reading growth in at least two ways: first, it further unpacked language minority status by providing a closer examination of children’s home language use by utilizing a “known groups” analytic approach—multiple-group latent curve analysis—to identify the different reading growth profiles due to language background; second, it then cross-validated these findings using an “emergent groups” approach—GMM.

Several results were noteworthy. First, convergent with prior research, language minority students shared qualitatively similar reading growth trajectories with their English monolingual counterparts comprising three distinct growth periods. LEP students, however, considerably lagged behind the other language background groups during each growth period. Second, the family SES-home literacy practices mechanism was most salient during kindergarten, and particularly for children with predominant English backgrounds, a finding divergent from prior research noting its salience across all demographics. Third, literacy instruction focused on phonics were found to benefit students with lower initial reading abilities (LEPs); however, no such benefits were discerned for bilingual students. Fourth, effects of ESL/bilingual programs (i.e., time allocated, in-class and pullout programs, and classroom aides) were mixed across the language background groups. Finally, the GMM analyses identified three latent reading profile groups, with EL students overrepresented in the low-achieving profile group. Students in this group were characterized as attending schools with lower reported involvement in school academic improvement processes, higher proportions of LEP students, and limited resources available for EL students. Limitations and concluding thoughts for future research are also discussed.

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Chapter 1 Conceptualizing the Research Problem

Thus far, the majority of research that has investigated children's literacy development has concentrated primarily on children who are native English speakers (for relevant reviews, see Adams, 1990; National Institute of Child Health and Human Development, 2000; Saracho, 2017). However, children speaking a home language other than English, the majority of whom are children of immigrants, constitute the fastest growing student population in the nation (over 20% of K-12 students, Capps, Fix, Murray, Ost, Passel, & Herwantoro, 2005). Language minority students are noted as a special status group in U.S. schools and flagged for linguistic assessment and identification upon enrollment (Abedi, 2008; Mahoney & MacSwan, 2005; Tamer, 2014) as well as for possible placement in linguistic support services (i.e., English Language learners, or ELs). Notably, language minority status is largely associated with English language status, as school districts in the U.S typically label these children as needing language support upon school entry based on household survey indicating their non-English language background (Bailey & Kelly, 2013).

Language minority children are a diverse group, highly variable in terms of their socioeconomic status, first-language practices, and experiences with literacy (Leventhal, Xue & Brooks-Gunn, 2006). They often encounter functional language difficulties, such as learning to use a new language to communicate for various purposes (Saracho, 2017). Thus, meaningful statements about intergroup comparability between ELs and English monolinguals must do more than rely on simple comparisons and generalizations; they must account for variability. The purpose of this study, therefore, is to examine the heterogeneity induced by students' diverse home language backgrounds and experiences with respect to their early literacy skills and reading growth over time. In particular, it is the intersection of family social class, language minority status, and EL status that draws my research interest in unraveling the complexity embedded within the multiple learning contexts in which these children are situated. In contrast to previous research that implies student reading development can be represented as a single homogeneous population, the analytic approach advanced in this study is that student growth in this domain may be better conceptualized as reflecting subsets of known and unknown groups that reflect considerable heterogeneity within the larger population (Muthén & Asparouhov, 2009).

Background of the Study

There is a dearth of studies that focus on children speaking a language other than English (e.g., August & Shanahan, 2006), as these children are often subsumed under a broader "at-risk" category, making it difficult to understand underlying learning processes or to tease out relevant differences. Oftentimes, there is a tendency to extrapolate implications for the education of language minority children based on the broader population of children. In some examples of the extant research studies on young language learners, authors employed the universal principle: if it works for mainstream children, it must work for language minority children and English language learners. Yet, studies noted the achievement gap between language minority children and English monolingual children persisted even after five to six years of schooling in the United States and was exacerbated by a constellation of factors that constrain language minority children's opportunities to learn (Ballantyne et al., 2008; Reardon & Galindo, 2006). Language minority children were more likely to live in high poverty communities and thus were more likely to lack access to health care services and to libraries and enrichment opportunities; they were also less likely to attend preschool (Ballantyne et al., 2008; Dolan, 2009), where forms of support were found to have a positive influence on children's early learning (National Research Council, 2001).

Given the vulnerability of these young learners, further research is needed on language minority children regarding how early literacy acquisition unfolds. In particular, more attention needs directed toward how home language background may moderate the learning experiences and literacy growth in children's early elementary years, as it carries implications about children's language dominance and hence, to some extent, English language proficiency levels (see Han, 2012). In addition, bilingual services in formal school settings need to be examined for these language minority children with respect to their effectiveness in supporting their reading achievement and growth. Presently, much of what is known either is based on short-term studies that stress English acquisition over the continued use of home language or school district datasets where language minority children's literacy proficiency is severely undermined by the classification of EL and non-EL students only (August & Shanahan, 2006; Genesee, Lindholm-Leary, Saunders, & Christian, 2006; Kindler, 2002).

In conceptualizing the language acquisition, there are two broad and largely different approaches. The first approach begins with the theoretical premise that language acquisition is a product of mental processes that take as their input information from the environment and produce as their output the ability to use and understand language (Hoff, 2006, 2013). The second approach, more common in the study of social and cognitive development than in the study of language development, has its theoretical underpinning in the bioecological model of development, which focuses attention less on the internal processes underlying development and more on the shaping role of the social contexts in which children live (Bronfenbrenner, 2005; Bronfenbrenner & Morris, 2006). This latter approach forms the backdrop of the current research effort, with the focus on an array of sociocultural variables relating to language minority children's literacy and language development. Ecological developmental systems frameworks propose ways in which social environments may interact with one another in ways that may attenuate or amplify their effects on social and cognitive development. The goal of the study is to further our understanding regarding the role of environmental supports in explaining students' literacy development, in particular, examining how language acquisition mechanisms may be influenced by differential supports in explaining language minority children and EL children's literacy development.

Previous research documented a wide array of factors contributing to language minority children's academic and learning outcomes, such as race/ethnicity, nativity status, socioeconomic status (SES), and EL status (De Feyter & Winsler, 2009; Jung, Fuller, & Galindo, 2012; Lee, 2002; Hopkins, Lowenhaupt, & Sweet, 2015). Each of these factors created a social category with demonstrated consequences for language minority children's divergent academic outcomes (Portes & Rumbaut, 2006). For example, a preponderance of extant evidence indicated that low SES and EL status were associated with language minority children's underperformance in school and widening academic gaps relative to their middle- and upper-class monolingual English peers (e.g., Fry, 2008; Gandara et al., 2003). Yet, mounting evidence began to acknowledge the unique strengths and advantages conferred upon these language minority children. Biliteracy and bilingualism, for example, were found to contribute to children's higher cognitive functioning and increased achievement scores (Bialystok, 2001). Yet, such findings needs to be understood in the context of children's socioeconomic background as some studies evidenced the negative effects associated with speaking home languages in low-income families (e.g., see Cummins, 2001).

Challenges in defining family SES. One of the challenges in understanding language minority children's academic outcomes, particularly with regard to literacy development, is how to best capture the family socioeconomic circumstances, as numerous previous studies demonstrated a robust relationship between family SES and children's early literacy development (e.g., Bradley & Corwyn, 2002; Hoff, 2006, 2013; Sirin, 2005). These studies pointed out several important ways in which family SES was related to children's early literacy attainments, including the learning environment, access to educational materials, language and literacy practices, and the breadth and quality of parent-child interactions. Further, prior research argued that SES-related differences in language development must be carefully examined and qualified by a description of the language outcome, the method of measurement, and the range of SES variables under consideration (Hart & Risley, 1995; Hoff, 2006; 2013); yet what those specific, and optimal, descriptions are remain unclear from the literature. As Fuligni and Yoshikawa (2003) cautioned, traditional measures of SES may fall short of capturing the varied socioeconomic circumstances of immigrant families and therefore may not be sensitive in explaining early educational outcomes. Immigrant parents' human capital (i.e., education attainment) may be underestimated compared to their American counterparts with regard to educational aspirations, for example, when considering parents who come from countries where fewer people have access to quality educational services.

Despite the evidence regarding the importance of family SES in explaining students' language development and literacy outcomes, there is a need for further research regarding the effects of SES on literacy development, where SES is defined in more than the most rudimentary way. Previous studies typically used simple proxies for SES, such as participation in the federal free/reduced lunch program, defining SES as simply two categories (not eligible or eligible).

Although such measures were more conveniently obtained, they are questionable in terms of reliability and validity, as this simple categorization often results in considerable measurement error (Harwell & LeBeau, 2010). More comprehensive measures of student SES should include multiple indicators including income, parent education level, and occupational status (Ensminger & Fothergill, 2003). Previously, however, such measures were not readily available, and when they were available, researchers typically combined several measures into one variable (e.g., such as by constructing a single factor score), rather than modeling the indicators as separate influences on student literacy development (Cowen et al., 2012). Unfortunately, the majority of previous studies examining SES effects on language development were conducted in monolingual samples with cross-sectional data, and the few studies that included low-income immigrant children typically provided less clear-cut results on the role of SES in explaining academic development (Duursma et al., 2007; Leseman & van den Boom, 2000; Oller & Eilers, 2002). Further research is therefore needed regarding the manner family SES is best operationalized in language minority achievement research and how it relates to language minority children's literacy development over time.

Over-reliance on monolingualism. Recent research on English language acquisition among language minority children criticized the traditional theoretical lens on which prior research was based; in particular, the premise that monolingualism was the norm, and hence, language minority students were by definition language deficient from the onset of their entry to formal schooling (August, Shanahan, & Escamilla, 2009). A prevalent assumption was that language minority children's low academic achievement resulted from speaking a language other than English (Hoff, 2013). Research indicated that students who were identified as requiring English language services and subsequently placed in English as a Second Language (ESL) services demonstrated significantly lower academic outcomes (Callahan, Wilkinson, & Muller, 2010; Umansky, 2014). As several studies noted, a by-product of such ESL placements was that EL students were poorly prepared academically because they had little access to mainstream curricula or native English speakers (Umansky, 2016; Valdés, 2001). Unfortunately, this type of academic segregation reinforced social stratification (García Coll & Szalacha, 2004). Clearly, such research provides evidence that school-based linguistic status (i.e., EL status) is an educational marker that places language minority children in a socially marginalized position, subject to bias and discrimination and that impedes their normal academic progress.

Accounting for sociocultural and linguistic diversity. Consideration of linguistic, socioeconomic, and immigrant status simultaneously adds complexity to the empirical inquiry. Although not all children of immigrants are language minorities, most young language minorities are children of immigrant parents (Gershberg, Danenberg, & Sánchez, 2006), especially those identified by schools as in need of language support services (i.e., ELs). In addition, because U.S. schools were often segregated along the dimensions of race/ethnicity and social class (Oakes, 2005; Orfield, 2005), immigrant and language minority children were overrepresented in schools with crowded classrooms, high proportions of minority students, and inadequate academic resources (Crosnoe & Fuligni, 2010; Palardy, 2008). The effects of such systemic segregation on educational processes including access to resources, academic expectations, and quality of educational experiences are far-reaching and complex. Integrating language minority status and school-based linguistic status into studies of academic achievement has the potential of expanding our understanding of how school resources are structured for these socially and historically marginalized children, as well as identifying the linkages between family socioeconomic status, home literacy practices, and children's literacy development.

Compared with monolingual English speakers, language minority children face increased academic challenges because they need to master English language skills and curricular content simultaneously (Scarcella, 2003; Genesee et al., 2006). Research found some subgroups of language minority children, such as Spanish-speaking ELs, were at elevated risk of falling behind academically because disproportionately high numbers live in poverty (Capps et al., 2005). Research also documented that the composition of students in a school, such as their mean socioeconomic and ethnic composition, can influence student learning beyond the effects of individual student characteristics (Crosnoe, 2009; Potes & Hao, 2004). Such compositional effects were construed as proxy variables for differential student access to resources, academic expectations, and quality of educational experiences. In particular, some schools were found to be "triply segregated," with high proportions of minority students, EL students, and low-income students (Crosnoe & Fuligni, 2010; Gándara, 2010). The negative effects accrued from living in poverty and attending high-poverty schools likely contributed to the low achievement of these language minority students.

The relevance of school language programs. Part of understanding the effectiveness of learning environment for language minority and EL students is the different types of English language programs available and provided to them. In practice, schools implemented both English-only and bilingual instructional approaches, with the latter approach identified as more beneficial, as it supported the simultaneous development of both English and the native language (August & Hakuta, 1997; Valentino & Reardon, 2015). The strongest evidence supporting this claim comes from randomized studies, which indicated a moderate effect in favor of bilingual instruction (Farver, Lonigan, & Eppe, 2009; Genesee et al., 2006). However, recent evaluations of scientifically based beginning reading programs used to teach non-English-speaking children to read in English showed promising results, suggesting that if children received strong language instruction with appropriate scaffolding, they were able to master early reading skills in English (August & Shanahan, 2006). This finding is consistent with the hypothesis that the amount and quality of language input children receive affects children's language development. Moreover, D'Angiulli, Siegel, and Maggi (2004) found that literacy-intensive programs can reduce the negative influences of low SES background on students' word-reading development. Together, these studies underscore the necessity of designing and providing appropriate language assistance to language minority and EL children based on their differential language and academic needs.

The conflation of SES, language minority status, and EL status has gained traction when studying minority learners' reading achievement. The confounding effects of SES background and language minority status in many analyses of reading achievement, such as those based on National Assessment of Education Progress scores, make it difficult to determine whether the apparent effects of language minority status are indeed a result of influences related to poverty. Some evidence accumulated that differences between language minority learners and their English monolingual peers were minimal in studies where the two groups were matched on family SES (e.g., Lesaux, Koda, Siegel, & Shananhan, 2006). However, some research also showed that the deficiencies in English oral language prevalent among language minority learners likely constrained their English reading development, and such deficiencies were less common or less pronounced among English monolinguals exposed to greater amounts of English at home, controlling for poverty status (Lesaux, Crosson, Kieffer, & Pierce, 2010; Lesaux, Rupp, & Siegel, 2007). A common argument for promoting the education of language minority learners is that the effects of poverty may be greater for language minority learners than for their English monolinguals at school, as limited English proficiency may deter them from accessing quality instruction or educational resources meant to ameliorate the effects of poverty (Gándara, Rumberger, Maxwell-Jolly, & Callahan, 2003). Kieffer (2008) found that language minority status mitigated the negative effects of school poverty, with smaller differences observed between language minority children with limited English proficiency and their English monolingual peers in high-poverty schools than observed among students in low-poverty schools. Together, these studies suggested it is important to understand how school and family poverty intersects with English proficiency status in influencing language minority students' achievement of reading.

Expanding methodological options. In the current literature concerning school effectiveness, heterogeneity in students' learning outcomes is commonly expressed in terms of random intercepts and slopes at the school level (see Muthén & Asparouhov, 2009)—that is, as a single achievement level or slope effect (such as the effect of SES on achievement) that varies across a single distribution of schools. As Muthén and Asparouhov argued, however, this approach is often misleading, as it assumes the sample is drawn from a single population characterized by a single set of parameters (e.g., means, variances, and covariances). In other words, the population is homogenous with respect to the relationships between variables, which has been described as a variable-oriented approach (Laursen & Hoff, 2006, p. 379).

More recently, a line of research began to address limitations of this conventional approach by utilizing a person-oriented approach (i.e., growth mixture modeling, GMM), which relaxes the assumption of a single distribution and facilitates the identification of emergent subgroups of individual growth trajectories which vary around different means of growth parameters (Bauer & Curran, 2004; Muthén & Asparouhov, 2011). Essentially, GMM captures the unobserved heterogeneity within the data by extracting a number of latent classes and calculating the posterior probability of class membership for each individual (Muthén & Muthén, 2000). Utilizing this new framework, some educational researchers examined both cognitive and non-cognitive performances (e.g., Chen, Hughes, & Kwok, 2014; Muthén, Khoo, Francis, & Boscardin, 2000). Importantly, this approach is critical in the substantive pursuit of "un-mixing" subpopulations of observations that differ (Parlady & Vermunt, 2010). Therefore, this approach is well-suited for exploring and examining theoretical propositions concerning the heterogeneity existing among language minority students in terms of, for instance, home language use patterns and English proficiency levels (Kieffer, 2008, 2010; Lesaux et al., 2010).

Research Focus

Extant research on immigrant and language minority students' achievement centers on adolescents as opposed to younger children during their early school years (e.g., Hao & Woo, 2012; Crosnoe & Lopez-Turley, 2011). As Crosnoe and Lopez-Turley (2011) noted, one reason for this imbalance is data availability: national data collection on secondary education is more common, whereas data on elementary education were, until recently, either nonexistent or poorly suited to studying children from immigrant families. State and local studies followed immigrant children during their elementary school years, but these samples often lacked within-group racial and ethnic, socioeconomic, and geographic heterogeneity (Suárez-Orozco, Suárez-Orozco, & Todorova, 2009). Thus, the nationally representative Early Childhood Longitudinal Study-Kindergarten Cohort (ECLS-K) is a valuable resource for examining the academic progress of children with diverse language backgrounds. Despite some limitations in data collection (e.g., the reading test was only provided in English and there was limited information regarding students' generational status), previous analyses using ECLS-K illuminated early disparities related to immigration, and trends in immigrants' early elementary school trajectories were found to differ from their secondary school trajectories (Crosnoe & Lopez-Turley, 2011).

Furthermore, it is important to note that there are a number of previous reports based on district-, state-, and federal-level data on the reading achievement of EL students (e.g., Kindler, 2002; Thomas & Collier, 2002). Although relevant for informing policy makers' decisions, data collected for monitoring progress and accountability are of limited value in advancing researchers' understanding of the reading development of immigrant and language minority students. First, these reports generally reflect data from only one subset of immigrant children, namely, those learners who meet the district criteria for the limited English proficiency (LEP) classification. These EL students are considered to have the lowest levels of English proficiency and thus receive additional support for language development. Yet, other EL students whose academic achievement is not represented in these datasets include students whose English proficiency was sufficiently developed such that, upon school entry, they were not classified as LEP. Also not included, there may be students who, although initially classified as LEP, progressed in language proficiency to a point where they lost their LEP label. It is crucial that research is not limited to one specific subset of immigrant and language minority students.

Furthermore, school districts tend to operationalize and define EL status differently, thereby inducing additional sources of error in studying language minority students' reading growth. As Bailey and Kelly (2013) noted, the reliability of EL designation and replacement depends upon the state they are in, the type of screening instruments they are administered, and the cut-off standard used in that academic year. As ECLS-K made use of information from school districts with regard to the EL designation and classification, it is hence likely that one student labeled as EL in one state may be considered as non-EL in another state. In view of this discrepancy, it is critical to examine whether there is unobserved heterogeneity present in the students reporting speaking a language different from English at home, as this information is often gleaned in the home survey in most states.

A number of previous studies clearly documented that the achievement of language minority children lagged behind the achievement of their native English-speaking peers in all content areas and that these students on average fell further behind with increasing years of schooling, as reading comprehension came to dominate all aspects of curriculum (de Jong, 2004; Gándara et al., 2003; National Center for Education Statistics, 2010). Indeed, these children face the challenge of negotiating two (or more) languages and must learn to analyze and comprehend sophisticated tests in a language in which, in many cases, they are not fully proficient. Our current understanding of the process contributing to reading comprehension, however, is based predominantly on research with native English speakers (see August & Shanahan, 2006; National Reading Panel, 2000). Regarding specific research on language minority students, the vast majority of studies are cross-sectional in nature and do not include native English speakers as the comparison group (for a review see Lesaux et al., 2006). Thus, there is a need to investigate the factors that influence reading development of language minority children over an extended time period vis-à-vis their English monolingual peers. As noted, by sampling the entire population of immigrant and language minority learners and measuring their English proficiency prior to school entry, a longitudinal analysis has the potential to illuminate how various background and school factors may contribute to their later reading development. Understanding this issue is fundamental to investigating how schools in the nation are meeting the academic needs and further educational and career opportunities of this rapidly growing population.

Research Purposes

The present study examines the literacy progress and reading achievement of children from kindergarten through grade 8, focusing primarily on their family SES, home language background, EL status, and school contexts and processes by utilizing a national longitudinal dataset collected by National Center on Education Statistics (NCES). The dataset for this study–the Early Childhood Longitudinal Study-Kindergarten Cohort 1998-99 (ECLS-K)–is well suited to the goals of the study, since it allows researchers to examine within-group racial/ethnic and socioeconomic differences by oversampling certain subgroups (i.e., Asians and non-White Hispanics). It also consists of several waves of data collection, which provides a unique opportunity to examine literacy growth over several key developmental periods. There are four research purposes:

- First, to describe the literacy growth trajectories of immigrant students relative to their nonimmigrant peers; further, to disaggregate immigrant students' diverse language backgrounds by a close examination of their home language use patterns and the timing of passing an English proficiency test. In particular, reading growth is examined across early elementary grades compared to later elementary and middle school years to determine whether one overall growth parameter or multiple growth parameters best capture the students' literacy development.
- Second, to formulate a formative latent factor regarding family SES and examine its differential effects on literacy achievement growth for children of different language backgrounds; further, to investigate whether SES effects on literacy progress are mediated by parent literacy practices across different language profile groups;

- Three, to examine the effects of types of ESL services available in the classroom, as well as teachers' coverage of key literacy skills, during kindergarten and first grade on student early literacy development;
- Four, to examine whether there are qualitatively different subpopulations of reading trajectory classes with respect to students' English language (EL) status using growth mixture modeling to capture the unobserved heterogeneity; and then to assess the indirect and mediating effects of school variables (e.g., EL-related processes, EL staffing and student composition) on the formation of group membership. This can aid in identifying the academic needs for different language profile students as opposed to a simple treatment of language minority students as EL or non-ELs.

Research Questions

These research purposes lead to the following research questions:

1. What is the shape of reading growth trajectory from kindergarten to eighth grade for students with different language backgrounds? Are there qualitative and quantitative differences with respect to reading growth across language background groups?
2. How do family SES and home literacy practices interact with language background to influence reading growth across children of diverse language backgrounds? What are the moderating effects of language background?
3. To what extent do classroom instruction practices and ESL programs contribute to reading growth from kindergarten through grade three with respect to language background?
4. How many unobserved groups with similar reading trajectories are expected? How are these latent groups expected to differ with respect to mean change, extent of inter-individual differences in change, and pattern of change? To what extent do school

contexts and processes impact the formation of latent reading trajectory classes, controlling for family background and classroom characteristics?

Organization of the Remainder of the Dissertation

The organization of the remaining chapters of this dissertation is as follows: Chapter 2 presents the three major theoretical frameworks that guide my research and the underlying rationale for using the statistical modeling approach, Multiple-group Latent Curve Analysis (MLCA) or Multiple-group SEM and Growth Mixture Modeling (GMM). Chapter 3 describes the study's methods, including information regarding the ECLS-K sample selection, key variables included in the analyses, and the latent growth curve and growth mixture models used in addressing the research questions. Chapter 4 presents the results of the study organized by research questions. Chapter 5 discusses the results of the study, limitations of the study, and the implications of the results for theory development and improved educational practices for immigrant and language minority children.

Chapter 2 Literature Review

In this chapter, I develop three major theoretical frameworks that guided my research, Bronfenbrenner's *bioecological model* (e.g., Bronfenbrenner, 2005; Bronfenbrenner & Morris, 2006), García Coll and her colleagues' (1996) *integrative model*, and *the family investment* model in early childhood (Conger & Dogan, 2007; Conger & Donnellan, 2007). Based on those theoretical frameworks, in Figure 2.1 I propose a conceptual model with major theoretical constructs as well as the linkages amongst them, such as socioeconomic status, language minority status, and family literacy practices. The direct and indirect effects of these variables on student growth in literacy are hypothesized to be nested within (or moderated by) students' home language backgrounds. A unique school context is assumed to surround the embedded individual and group processes summarized in the figure. In addition, the underlying rationale for the modeling approaches used in the analyses, multiple-group latent growth analysis (Curran & Bollen, 2001; McArdle & Hamagami, 2001) and latent growth mixture modeling (Masyn, 2013; Muthén & Asparouhov, 2009, 2011), are discussed regarding how they facilitate examining the inter-relationships of the multiple embedded contexts comprising the child, family, and school.

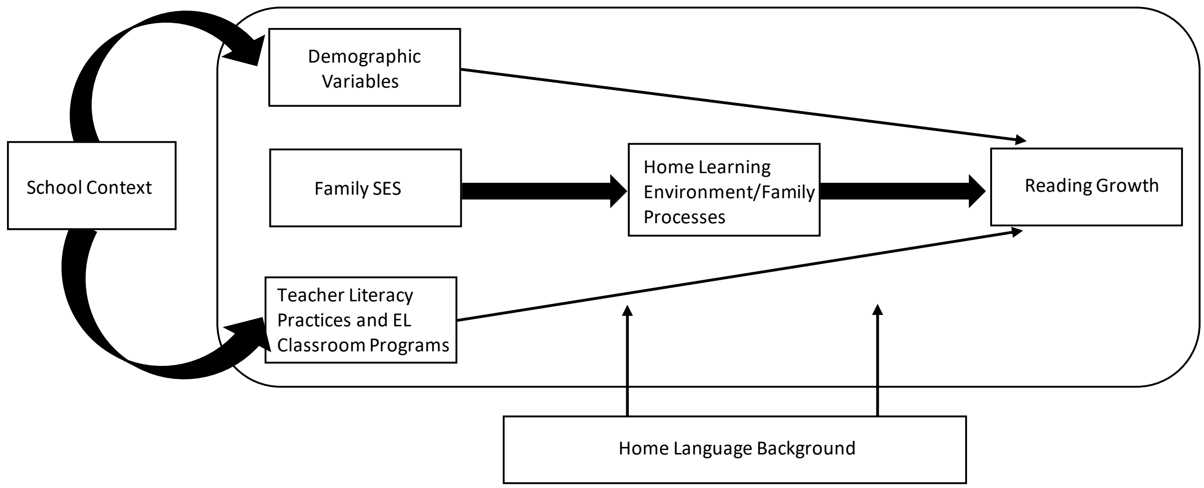

Figure 2-1 Proposed conceptual model

Theoretical Frameworks

Bronfenbrenner's bio-ecological model. The bio-ecological model primarily addresses the continuity and change in the biopsychological characteristics of human beings (Bronfenbrenner & Morris, 2006). Its scientific power was shown to be robust through a large number of empirical studies over the past few decades. There are four defining components—*process*, *person*, *context*, and *time*. The keystone of this model is the process construct, which encompasses particular forms of interaction between individuals and environment, also known as the proximal process. It is posited to be the "primary engine" that drives human development (Bronfenbrenner & Morris, 1998, p. 798). Further, Bronfenbrenner and Morris (1998, 2006) noted that the power of proximal *process* to influence development is presumed, and shown, to vary substantially as a function of the characteristics of the developing *person*, of the immediate and more remote environmental *contexts*, the nature of the developmental outcomes under consideration, and the *time periods* in which the proximal processes take place. Since one goal of my study is to investigate children's reading development from kindergarten through middle school, the bioecological model is an ideal conceptual framework to guide my research, through which I can derive specific propositions regarding the key variables and constructs as well as how they intersect synergistically in shaping children's reading growth trajectories.

In Figure 2.1, the home literacy environment can be construed as a proximal process through which the developing child interacts with parents through a range of literacy activities (e.g., shared book reading) and engages with objects and symbols (e.g., books and CDs), both of which are posited to contribute to her language development. Interpersonal relations and activities that occur in the immediate setting (home and school) including distinctive characteristic of personalities, temperament, and systems of belief constitute the critical features of the innermost region of the ecological environment—the microsystem (Bronfenbrenner, 2005). It is through the proximal process that features of person and context can bring about changes on the developmental outcome. Hence, in the study, I conceptualize home literacy environment as a proximal process mediating the relation between family socioeconomic status (i.e., a proxy for context) and children's language growth (i.e., a developmental outcome).

This mechanism has been tested in a large number of previous studies which found that the home literacy process had its greatest impact on children from more favorable environments (i.e., mid- and high socioeconomic status). The research suggested that SES-related differences in children's early language development were explained by SES-related language learning experiences manifested through the differing quality of maternal speech and varying degree of maternal responsiveness (Bornstein & Bradley, 2003; Hoff, 2006, 2013). Importantly, the findings indicated that maternal characteristics as well as parenting practices were essential in determining how SES is associated with children's developmental outcomes (Linver, Brooks-

Gunn & Kohen, 2002). This relationship also proved robust in a number of studies conducted across different ethnic groups (see Hoff, 2006).

A basic premise of the bio-ecological theory is that development is a function of forces emanating from multiple settings and from the relations existing among these settings (e.g., relations between home and school), defined as the next level of the ecological environment--the mesosystem (or school context in Figure 2.1). Although the family is the principal context in which children's early language growth takes place, it is but one of the settings that such development can occur. Moreover, the processes operating in different settings are not independent of each other, in the sense that events at home can affect children's progress in school and vice versa. A line of research utilizing the *family socialization model* exemplifies the interactive and dynamic processes taking place between homes and schools, especially during children's transition into elementary school (Gershoff, Aber, Raver, & Lennon, 2007). Family processes are most implicated in academic disparities during this period because, as children advance through school, the formal (e.g., curriculum) and informal (e.g., peer influences) processes of education account for increasingly large shares of such disparities. Moreover, previous research suggested advantages that accrue over time were reflected in widening achievement gaps, as some children were selected into better learning opportunities (Alexander, Entwisle, & Olsen, 2001; Tung et al., 2009). Where language issues are concerned, previous research noted low-income children typically suffered from imitation of nonstandard speech patterns, too little conversation with adults, too little practice to use language to express complex ideas, too little opportunity to develop reasoning skills, weak vocabulary development, too little experience with books, and little or no instruction and practice with phonological awareness and other pre-reading skills (Hoff, 2006; 2013). Thus, formal school entry is one key transition when family processes related to socioeconomic disadvantage likely have a pronounced impact on learning in ways that forecast long-term disparities.

Another distinct feature of the bio-ecologial model is *time*, which permeates the nesting structures of the ecological environment (micro-, meso-, exo-, and macro-system). The chronosystem model posits that life events or experiences that occur throughout the lifespan may serve as the impetus for developmental change (Bronfenbrenner & Morris, 2006). Specifically, the model distinguishes between normative experiences (e.g., school entry) and non-normative events (i.e., moving). An important life event occurring in the early childhood stage is when children change from “home child” to “school child.” Investigating children’s school achievement at the earliest possible point, when their life histories still are relatively abbreviated and their achievement patterns are first taking form, should offer important insights into the social forces that influence such achievement, including whether the salience of multiple settings shift over time (e.g., home literacy environment), particularly during children’s critical transition to formal schooling (i.e., from kindergarten through early elementary school years).

García Coll et al.’s integrative model. The integrative model addresses the core notion of social position in the context of studying developmental outcomes between ethnic minority children vis-à-vis their mainstream middle-class Caucasian counterparts. According to García Coll et al. (1996), the effect of social position on developmental outcomes is mediated through the pervasive social mechanisms of racism, prejudice, discrimination, and oppression—all which provide a segregated macro-system to which ethnic minority children are subject. Importantly, García Coll and Sazlacha (2004) contended it is not social category per se that influences development but, rather, the cultural meaning associated with that position that influences developmental processes; that is, the stereotypes, norms, and expectations about race/ethnicity shape development, rather than the social positions themselves. The integrative framework argues against the utility of the prevailing pattern of studying ethnic and cultural differences by comparing developmental outcomes, with little or no attention to the nature of the ecological context in which these outcomes occur or the processes through which they are achieved. Children from different subcultural groups may develop in a particular way found in the character of the micro-, meso- and exosystems[1] that are operative for that particular group (Bronfenbrenner, 2006).

Previous research produced evidence regarding the role cultural factors play in shaping children's language development. English monolingual children in the United States are often socialized early into the norms, values, and expectations of this mainstream Anglo-Western culture by their parents. Children with non-English-dominant backgrounds are also socialized into norms and values deemed important in their own cultures. For example, a study of Chinese Canadian mothers' beliefs about child-directed talk revealed that this cultural group held beliefs that were quite different from the beliefs of their mainstream Canadian counterparts (Johnston & Wong, 2002). When these children started school in the mainstream culture, they naturally brought to school the socialization patterns they learned at home, which were often translated into lower language skills perceived by teachers who shared similar mainstream beliefs with Canadian mothers. Such cultural differences and challenges were found to affect ethnic minority children's mastery of English language skills negatively, as documented in some ethnographic studies in the U.S (e.g., Lee & Bowen, 2006).

[1] Exosystem is not discussed here as it deals with relations between family and other settings that do not contain the developing person, such as parents' work place, community, or care centers, which are not part of the proposed conceptual model.

Further, for children whose primary home language is not English, the development of language and literacy involves the integration of component skills (e.g., sound-symbol awareness, grammatical knowledge, vocabulary knowledge), as well as more elusive sociocultural variables critical to the development of reading (Castro, Espinosa, & Páez, 2011). It is important to recognize that these language minority children are not only faced with challenges of acquiring English language proficiency but also becoming socially accepted by peers in the classroom—a phenomenon defined as "the double bind of second-language learning" (Tabors, 2008, p. 33). Oftentimes, teachers were not fully cognizant of the "social isolation and linguistic constraints" that language minority children encounter when placed in a setting where home language was not available to them (Tabors, 2008, p. 34). Fortunately, however, most young children were found to develop strategies for coping with this "double bind" and can adjust as some early childhood research suggested (Castro et al, 2011; Hoff et al., 2012). It remains unclear how children cope with such constraints when moving on to higher grades in elementary school, especially when language proficiency mastery becomes more urgent in order to perform well in reading achievement.

Family investment model in children's early literacy development. The family investment model is one relevant theoretical orientation addressing mechanisms by which family social class (i.e., measured by socioeconomic and social status indicators) may shape children's cognitive and socioemotional wellbeing (Conger & Dogan, 2007; Conger & Donnellan, 2007). In this model, three indicators of family SES—income, education, and occupation—are hypothesized to affect the likelihood of children becoming competent and successful adults, primarily through a specific mediating process involving socialization practices. This model, referred to as the investment model, posits that financially well-to-do families are more likely to invest in developing the child's human capital. In contrast, it proposes that children from economically disadvantaged backgrounds are faced with a constellation of social, economic and cognitive risks that may preclude direct investment in their children's human capital development.

The model's utility was demonstrated in several empirical studies which confirmed its basic proposition that higher family income during childhood and adolescence is positively associated with academic and occupational success later (e.g., Aikens & Barbarin, 2008; Bradley & Corwyn, 2001). Specifically, the positions of parents in larger structures and institutions of society shaped their parenting behavior, while also organizing their children's opportunities to learn. Bradley and his colleagues, for instance, demonstrated a positive association between family income and investments among several thousand children ranging in age from infancy to early adolescence when evaluating differences in parental behavior across different ethnic groups (Bradley, Corwyn, McAdoo, & García Coll, 2001). They found that parents in families with income above the official poverty guidelines, regardless of ethnic background, were more likely to engage their children in conversation, learning activities, as well as to provide greater access to books, toys, and cultural events and activities that stimulate learning than parents in families below such poverty guidelines.

Of increasing interest is the pathway through which parents' educational level is related to their child's literacy development. Two studies provided credible tests of a mediating pathway hypothesis in the investment model, that is, parent educational attainment affects children's literacy development (e.g., vocabulary size) via creating a stimulating learning environment and providing more literacy-oriented practices. In the first, an intensive study of 33 families in which both parents had received college educations and 30 families in which neither parent had gone beyond a high school education, Hoff (2006) examined the manner through which these educational differences affected the vocabulary development of two-year-old children. The findings showed that more highly educated parents created a richer, more complex language environment for their children. This environment included a greater variety of words, more verbal interactions, and more frequent mother responses to topics addressed by the child. Importantly, Hoff found that the richness of maternal speech completely mediated the association between parent education and child productive vocabulary.

In sum, language minority children's literacy development is multi-faceted and needs to be conceptualized in terms of the interaction between language input, process, and the sociocultural characteristics of the multiple environments within which child is situated. These frameworks help identify the variables of theoretically relative importance as well as guide my thinking in conceptualizing the possible interactions and relationships among them. Although sociocultural factors are important, to what extent their effects are translated into English proficiency and academic outcomes for language minority children remains challenging. Similarly, less is known regarding the mechanisms through which classroom practices or school ESL programs affect language minority children's academic reading outcomes. In the ensuing sections, I will review the literature pertaining to children's literacy and reading growth, especially among language minority families.

Examining Literacy and Reading Growth in Language Minority Families

Bradley and Corwyn (2003) used several waves of data from the National Longitudinal Survey of Youth to assess the impact of SES on cognitive and behavioral development from early childhood through early adolescence (i.e., data collected at three years old, six years old, and 15 years old, respectively). The investigators examined the degree to which the learning stimulation parents provide mediated the relationship between parent education and several outcomes. Findings suggested that at each age level, parent education was positively related to a child's vocabulary, reading, and mathematical skills and negatively related to behavioral problems. Moreover, for each age level and each developmental outcome, they discovered that the association between parent education and child development was reduced in magnitude once learning stimulation was added to the prediction equation. From these findings, they concluded that the parent's stimulation of learning mediated the relationship between education and child competence.

Mistry and her colleagues (2008) extended the investment model to immigrant families, with the intent of determining whether such mediating pathways were exclusive to mainstream nonimmigrant American families. In this study, Mistry et al. found that SES operated similarly across immigrant and native households; that is, SES was indirectly related to children's early literacy skills through home literacy practices. Notably, the researchers found maternal education, as opposed to family income and welfare receipt, was the strongest predictor of the composite of SES—a finding consistent with prior research (e.g., Hart & Risley, 1995; Hoff, 2006, 2013). However, Mistry et al. (2008) found the effect of SES on the mediating variable—home literacy practices—was stronger for immigrant families than for native families, partly because children in immigrant and low-SES families received less reading input in the host society's language (see also Prevoo et al., 2014). Yet, these findings need to be corroborated with longitudinal data, as the latter approach provides stronger evidence concerning the causal pathways of family socioeconomic status, home literacy practices and children's reading development across different language backgrounds.

Home language environment, English proficiency, and reading development. Although some researchers showed that bilingual classrooms and home environments contributed to higher early literacy skills (Genesee et al., 2006; Scheele, Leseman, & Mayo, 2010), others found that monolingual English children, learning only English at home and school, generally outperformed bilingual children of all backgrounds (Blackledge, 2005). The mixed results of these studies helped unravel the complex nature of bilingualism—that is, whether there were positive, negative, or null effects associated with children speaking two languages, and that the results, in part, depended on the levels of language proficiency children attain in both languages (Cummins, 1984b). Children with higher levels of bilingual proficiency were found to experience higher levels of cognitive abilities resulting from enhanced metalinguistic awareness or attentional abilities when processing information (Bialystok, 2001; Cummins, 1984b). The cognitive consequences of dual language learning were varied and depended on the circumstances of acquisition. For example, a number of studies supported additive or positive bilingualism, where the acquisition of a second language was not at the expense of home language (Bialystok, 2001). However, there was also evidence for the reverse situation, where children acquired a second language at the cost of losing facility with their home language—a situation referred to as subtractive or negative bilingualism (Oller & Eilers, 2002; Patterson & Pearson, 2004; Scheele et al., 2010). Taken together, these studies suggested that two mechanisms may both operate when children are learning two languages, and the circumstances under which children acquire two languages vary considerably.

It is unrealistic to for most children to achieve balanced bilingualism. The dominance of one language over the other—a condition in which bilingual children have greater grammatical proficiency (e.g., vocabulary), or greater fluency in one language, or simply opportunities to use one language more often (i.e., the dominant language)—is closely linked to the amount of language input a child receives in each language (Genesee, Paradis, & Crago, 2004). It is difficult to place bilingual children in a homogeneous group, as each child can have different degrees and contexts of exposure, and these can affect his or her developmental rate. A few small case studies found that bilingual children did not represent a single group at or below the lower bound as set by monolingual children, and, in fact, bilingual children demonstrated comparable growth rates with their monolingual counterparts in terms of phonological processing, word reading, and spelling (Aarts & Verhoeven, 1999; Carlisle & Beeman, 2000). Importantly, similar to monolingual children, bilingual children, varied considerably in their individual rates of development; some acquired language faster than others.

These results were further substantiated using large-scale longitudinal datasets. For example, Lesaux and her colleagues (2007) designed the first longitudinal study to investigate the reading developmental pathways from kindergarten through fourth grade for two subpopulations, ELs and native English speakers, using a wide range of cognitive and linguistic measures (e.g., working memory, sound mimicry, rhyme detection, and oral cloze) at each point in time. The ELs in the study spoke diverse home languages, such as Chinese, Korean, and Farsi. Importantly, Lesaux et al. found that the assessed tasks were strongly mediated by language proficiency, a finding consistent with some research that suggested English language proficiency was a key to academic success regardless of home language use (e.g., National Center for Education Statistics, 2010). A point of divergence appeared, however, regarding reading comprehension processes—ELs performed on par with their English monolinguals—although prior research indicated reading comprehension was a significant weakness in language minority learners (Verhoeven, 2000). The bilingual-monolingual differences in grammatical development were consistently documented for vocabulary size (Genesee et al., 2006). Notably, however, a key limitation of the Lesaux et al. study was the difficulty in ruling out extraneous variables in comparing results, as their data came from a single school district with relatively strong literacy instruction (e.g., vocabulary) which may have contributed to these EL learners' superb reading performance.

Several other longitudinal studies investigated the extent to which language minority students' English language skills at the time of school entry predicted differential growth in reading. For example, Kieffer (2008) grouped language minority students into two broad categories upon kindergarten entry—one with full English proficiency and the other with limited English proficiency—and compared them against the native English speakers regarding their reading growth from kindergarten through fifth grade. He found similar reading trajectories between English monolinguals and language minority children with full English proficiency but noted a consistent gap between these groups and language minority children with limited English proficiency. Importantly, the reading trajectories of language minority students with limited English proficiency were found to be on par with those students who shared similar demographic risk factors (i.e., were of the same ethnicity and SES). Further, Kieffer found language minority status moderated the negative effect of attending a high-poverty school. Together, these findings underscore the need to unpack language minority status by an up-close look at the intersection of ethnicity, SES, and English language status.

More recently, Han (2012) employed parent self-report measures with regard to home language use patterns and a standardized test for oral English proficiency to capture children's English language ability more thoroughly, as opposed to using a school-designated status alone as in Keiffer's (2008) study. Results revealed a similar pattern, however; that is, English dominant bilinguals and mixed bilingual learners' scores in reading and math were no different from their English monolingual counterparts. Non-English dominant bilinguals and limited English proficient students, however, still struggled with reading by fifth grade. Further, Han's study included a wide array of measures on school processes and resources available for language minority students. The results indicated limited English proficiency and, therefore, reduced access to the school's mainstream curriculum were characteristics that put Non-English dominant bilinguals and limited English proficient students at elevated risk of reading difficulties. Importantly, this study confirmed that language minority students of Latin and Asian origins with limited English proficiency often attended schools with limited resources and larger concentrations of low-income students, which compounded the risks associated with these students' reading development. Notably, this study, given its ingenuity in using a large-scale survey data to study the complex notion of bilingualism, was predicated on the assumption that English language proficiency can be explained through both a relative measure—home language use and an absolute measure—standardized English test, which may be problematic (Unsworth, 2016).

In summary, this line of research highlights the daunting task of operationalizing language experience as it concerns the length of exposure in English and home language, as well as the quality of language input, and this is exacerbated by the limited information available in the survey data. Further, although there was evidence regarding the presence of differential mechanisms of bilingualism among language minority children, whether positive or negative, they were found to vary dependent upon the family SES. For example, relatively more frequent use of home language was found to slow down language minority children's English acquisition in low-income immigrant homes but to increase English acquisition among those from more affluent homes (see Cummins, 2001). Moreover, home language background was found to explain a large portion of variation in young children's expressive language development and early reading between nativity groups (e.g., Han, Lee, & Waldfogel, 2012). Han et al. noted that parents with higher levels of English proficiency and who used English primarily at home were more inclined to expose their children in an English-speaking environment and were more apt at adopting the mainstream U.S. educational norms; hence, they were more likely to help their children get ready for school. Therefore, children's early literacy development is at the nexus of family SES background, home language environment, and parent literacy practices, each of which plays a critical role in shaping children's English literacy and reading development.

School contexts and reading achievement among language minority students. Critical to understanding the reading growth patterns for children of diverse language backgrounds is to examine the extent to which school contexts and processes affect their reading growth trajectories. English language status represents a primary attribute associated with most language minority students attending schools in the U.S., as they usually come to school with limited English language skills. EL status is a value-laden term designated by schools to structure learning resources within the classrooms. Previous research found EL status adversely impacted EL children's English language learning and reading development (Umansky, 2016; Valdés, 2001). More specifically, Umansky (2016) found that students classified as ELs in kindergarten had significantly lower test scores in math and English language arts in Grades 2 through 10 compared to their counterparts placed in mainstream English classrooms. This gap was sizable in second grade and grew slowly in magnitude as ELs progressed through elementary and secondary school. Several mechanisms can explain this relationship. First, the provision of specialized EL services can result in isolation from English-speaking peers in separate classrooms with little opportunity to converse in English during the day aside from interacting with teachers (Gandra et al., 2003; Gifford & Valdés, 2006). Second, the provision of EL services may crowd out participation in mainstream academic classes. A recent examination of EL policy practices in Texas revealed that courses designed for ELs (e.g., English Language Development) may substitute rather than complement core academic classes (Umansky, 2015). Third, EL classification may be linked to tracking practices that limit access to full academic participation of mainstream curriculum (Estrada, 2014; Kanno & Kangas, 2014). Essentially, this line of research substantiates the theoretical argument on social position, in that the cultural value and meaning attached to EL status can lead to systematic barriers that impede the normal academic progress of EL children's reading achievement.

Language minority students flagged as ELs typically are placed in English language programs, such as English-only programs, bilingual programs, and transitional programs, and the latter two are respectively considered as additive and subtractive forms of bilingual education (Genesee et al., 2004). Although both native language and English are used in these programs as media of instruction, they have different purposes insofar as the first one aims at maintaining both languages, whereas the latter one uses home language until one can achieve adequate understanding in academic English instruction. Previous research on the efficacy of bilingual education were mixed. On the one hand, research suggested that children participating in bilingual education performed as well as, sometimes better than, their counterparts participating in English-only programs or transitional programs (e.g., Lindholm, 2001; Thomas & Collier, 2002). On the other hand, however, there were no evident advantages or disadvantages for language minority children participating in bilingual programs. In these cases, language minority students were shown to perform at a similar level with their counterparts in English-only programs or at par with state-level or district-level standardized test results (for a review of studies see Lindholm-Leary & Borsato, 2006). Together, these studies show that schooling with students' native language does not hamper their English development compared to language minority students in all-English programs.

Student body composition in terms of concentration of students with limited English proficiency has often been conceived as a proxy for instructional services and support provided in schools (Han, 2012; Han & Bridglall, 2009; Zehler et al., 2003). Han and Bridglall, for example, examined the achievement growth of EL students within three concentrations of EL schools (i.e., no EL students, low concentrations, high concentrations), noting a reduction in the size of kindergarten gaps in reading growth trajectories by fifth grade for EL students versus non-EL students attending schools with higher EL concentrations. In contrast, EL students who were in schools with no reported EL services had consistent reading achievement gaps throughout their elementary educational years. The researchers attributed the differing results to the presence of targeted school resources. More specifically, they found the presence of Title I services (e.g., extending learning time before and/or after school for targeted children, family literacy services) and services for EL families (e.g., translators available for parent–teacher conferences, outreach workers to assist families enrolling children) allowed EL students to improve more quickly than their peers not receiving such services. In another study of features of ELs' schools, school environments (e.g., with greater teacher effort and better physical resources) were highlighted to account for variance in between-child differences in EL students' reading growth, although to a lesser extent than child and family background (Han, 2012). Of note, among school process variables, the increased quality of the learning environment primarily influenced changes in EL students' reading scores positively. As a whole, these studies underscore the importance of teachers in shaping children's academic trajectories, particularly for children designated as ELs.

Importantly, the educational resources available at school may make a larger impact on language minority children's learning outcomes compared to their peers, as language minority learners may have less social capital, cognitive stimulation, and English language input at home and hence benefit more when they can tap such resources at school. A critical transition occurring from home to school not only presents challenges in acquiring a second language used by the large society but also subjects language minority students to a culture different from their own. As children move from preschool into kindergarten and the primary grades, classroom instruction emphasizing phonemic awareness, letter recognition, segmenting words into sounds, and decoding printed text are building blocks to support later reading competence (Saracho, 2017). Deficiencies in English literacy skills may prevent EL students from accessing educational programs or resources meant to ameliorate the risk factors associated with their language minority status, largely due to the institutional barriers and perceived bias. In this layered view of students' language backgrounds, school contexts, and available English language services, it is important to make use of the dataset that contains language minority children attending varying school contexts and examine how these school settings and processes affect their reading trajectories.

Studying Student Literacy and Reading Growth

As the review of substantive studies concerning background, family, and school variables on student literacy growth demonstrated, there is a further need for examining longitudinal data regarding students' literacy and reading development over time. The development of proper methods to examine individual development challenged researchers in the past due to inadequate design, measurement, and inability to incorporate different times of measurement and missing data into the analyses (Raudenbush & Bryk, 2002). Two current approaches able to incorporate differential times of measurement and missing data are random-coefficients growth modeling and latent curve growth analysis (Willett & Singer, 2003).

Latent curve analysis. Latent curve analysis, a longitudinal data approach within the framework of structural equation modeling (SEM), is well suited to assess developmental changes in longitudinal panel data, as it (1) accounts for the clustering effect inherent in the repeated measurement design; (2) adjusts for the measurement error in covariates (see Muthén & Asparouhov, 2009); and (3) provides flexibility in capturing the different reading growth profiles for subgroups of language minority children and their native English monolinguals peers over several distinct time periods (see Meredith & Tisak, 1990; Muthén & Muthén, 2000). The latent curve approach is especially useful where the focus of the research is to identify multiple growth periods (referred to as piecewise growth models), and where there is an interest in determining the suitability of a particular model across multiple groups. Latent curve analysis is also useful in identifying subgroups of individuals who may share particular growth trajectories, where the subgroups are not known ahead of time but, rather, emerge from the data examined (Ram & Grimm, 2009).

Measurement invariance is a key assumption that needs to be satisfied when making valid conclusions about the changes in individuals occurring across time (Curran & Bollen, 2001; McArcle & Hamagami, 2001). More specifically, when researchers test whether a measure is invariant, they are investigating whether the construct has factorial invariance (Byrne, Shavelson, & Muthén, 1989); that is, the latent factor scores were generated in a similar fashion across groups, thus producing metric invariance (i.e., regarding the unstandardized factor loadings) across groups (Sass & Schmitt, 2013). Scalar invariance evaluates whether the observed variables metric (i.e., intercepts) are relatively equal across groups. In a similar vein, structural invariance is key to assessing whether the relationships between covariates and latent factors change across multiple groups, in that, the differences in the effects of path coefficients can be interpreted as meaningful differences existing among groups of children with diverse language backgrounds (Sass & Schmitt, 2013).

A typical latent growth model is presented in Figure 2.3, which shows four manifest variables—scale scores time 1 through time 4—which were placed in boxes to denote them as manifest or measured variables. These four variables represent scores on a particular scale for individuals in a longitudinal investigation with four equally spaced times of measurement. In this figure, two latent variables are shown in circles—Level and Slope. The Level latent variable has a path to each manifest variable, and these path coefficients are all fixed at 1.0. The Slope latent variable also has paths to the four manifest variables, with coefficients labeled β_1-β_4. At least two of the paths β_1-β_4 must be fixed to identify the model, and all four paths can be fixed. Often, β_1-β_4 are fixed to 0, 1, 2, and 3, respectively, resulting in a Level latent variable that represents each person's estimated outcome level at time 1(i.e., initial status), and a Slope latent variable that reflects estimated linear growth or change for each person after time 1.

Different alternatives for coding the coefficients of the Slope latent variable, with utility in interpreting developmental trends, were described by Biesanz, Deeb-Sossa, Papadakis, Bollen, and Curran (2004). Notably, however, one shortcoming of the latent growth model in Figure 2.3 results from the use of a single score for each person at each occasion, a shortcoming shared with ANOVA. With only a single score at each occasion, however, the model begs questions regarding factorial invariance, relying instead on the assumption that the same construct is assessed in the same metric at each occasion (Widaman, Ferrer, & Conger, 2010).

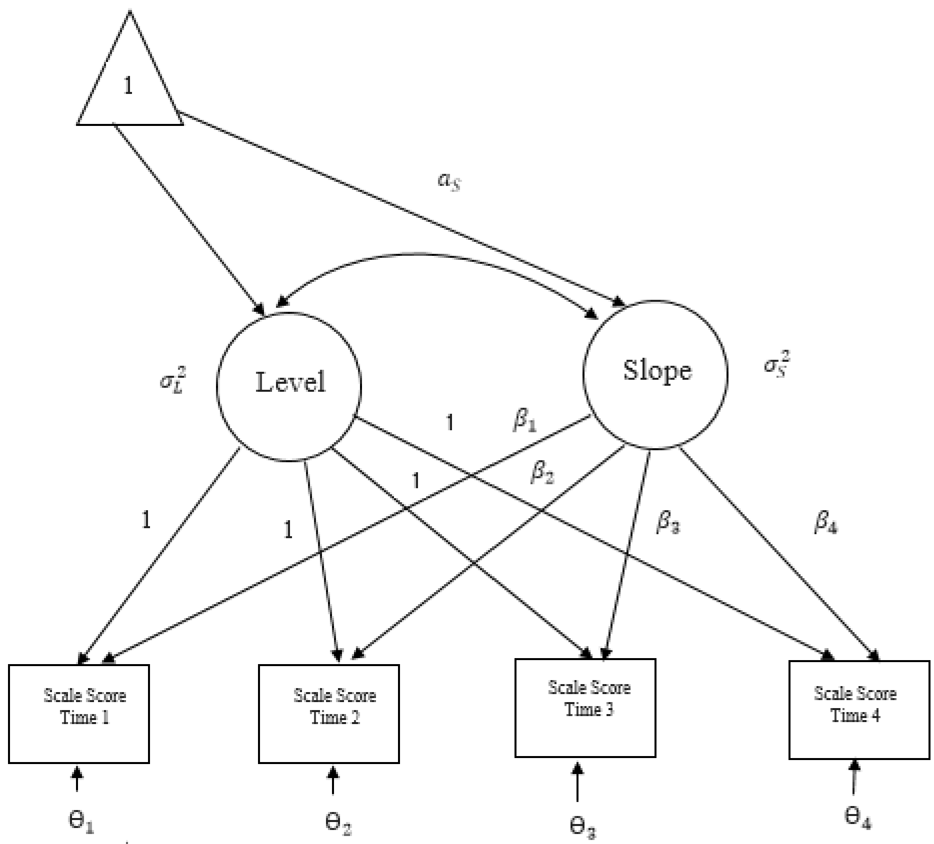

Figure 2-2 First-order latent growth model specified for four manifest variables, consisting of one manifest variable at each of four times of measurement.

Examining growth across multiple groups. The longitudinal and multiple group nature of the data structure in the current study requires research methods that accommodate the multiple random effects associated with growth parameters across individuals nested within groups. In a typical growth analysis, language background is treated as an individual-level covariate, and its interaction with time-related scores is used to explain both inter- and intra-individual variation in growth trajectories (Han, 2012). A major drawback with this typical approach is the inability to detect the variability in growth associated with each language background group specifically, as the multilevel regression approach or the latent growth modeling approach provide a set of common covariate population parameters for all individuals in the sample (Muthén & Asparouhov, 2011).

In contrast, there are several advantages of placing the growth model in a multiple-group SEM context, such as the rigor of studying multiple groups with respect to the growth rates of individuals within each group examined, as well as the examination of possible differences in the structural relationships between covariates and growth factors. The focus of such analyses is to identify parameters that may be invariant across groups as well as those that may be more group specific. In the current study, for example, this approach facilitates conducting a series of tests concerning how family SES operates within each language profile group in relation to home literacy practices and children's early literacy growth.

In my study, I conceptualized language background as a moderator in modeling relationships among child characteristics, family backgrounds, and classroom settings. Of key interest is whether the mechanisms underlying family social class, home literacy practices, and reading growth outcomes found in the literature are congruent across different linguistic minority children, as there has been some evidence suggesting otherwise (Mistry et al., 2008). This entails analyses of factorial invariance and structural invariance that are integral to ascertaining the ways in which these meaningful differences in growth patterns arise among different groups (Sass & Schmitt, 2013), in this case, language profile groups. This multiple-group SEM approach, therefore, facilitates understanding the unique pathways relating family SES, home literacy practices, and reading growth outcomes among linguistic minority populations. Further, this modeling approach circumvents the issue of forced choice of a reference group—typically non-Hispanic Caucasians in order to facilitate comparisons regarding achievement gaps existing between mainstream English monolinguals and their counterparts with non-English backgrounds (see Han, 2012). Essentially, a distinct advantage of multiple-group latent growth analysis is that researchers can investigate the heterogeneity induced by children's diverse language backgrounds that has oftentimes been obscured by treating it simply as a dummy variable at the child-level portion of the model.

Growth mixture modeling. Multiple-group analyses are appropriate if the interest is to compare explicitly defined groups beforehand; however, there is a model-based approach that helps identify the number of subgroups of populations of interest, such as factor mixture models (Lubke & Muthén, 2005; Nagin, 1999). Usually, school districts or schools have inconsistent ways of identifying English language learners and as a result, a student classified as EL in one state or district may not be considered as EL in another (Linquanti & Cook, 2013). Further, it is recommended that school districts need to operationalize EL definition depending on the levels of students' linguistic and academic performance (Cook, Linquanti, Chinen, & Jung, 2012). The ECLS-K data utilized in the present study was limited with respect to defining EL status because it was a national study, with EL status only broadly defined as whether or not students received English language services in their classrooms and schools (Tourangeau et al., 2009). This limited definition likely masked the considerable variability existing in its definition across the sampled schools and districts.

A contrasting approach, factor mixture analysis, is well suited to investigating the unobserved heterogeneity in the context of the study providing only limited information on students' EL status. The factor mixture model combines the latent class model and the common factor model and has a single categorical and one or more continuous latent variables (Lubke &

Muthén, 2005). The categorical latent variable serves to model the unknown population heterogeneity. Extending this model framework to longitudinal panel data analysis, growth mixture models capture information about inter-individual differences in intra-individual change, taking into account unobserved heterogeneity by relaxing the assumption that one set of parameters can describe the growth trajectories between individuals and allow for different groups of individual growth trajectories to vary around different means of the growth parameters (Bauer & Curran, 2004). As a result, each latent class can have its unique estimates of variances and covariate influences, and such flexibility is the basis for the related GMM framework (Muthén & Muthén, 2010). Importantly, GMM is an exploratory approach that should be guided and constrained by theory (Ram & Grimm, 2009).

Compared with traditional cluster analysis and similar alternative techniques (e.g., Nagin, 1999), growth mixture analysis provides a number of advantages (McLachlan & Chang, 2004) in the context of this study. First, it represents a model based clustering method where cases are classified in a probabilistic manner. The probability of belonging to each class in a given model is computed, and individuals are assigned to the class for which they have the highest probability of membership. Second, this approach facilitates including exogenous variables, or covariates, in the model. In so doing, the predictive relations between the covariates and class membership also become model-based rather than post-hoc estimations. Third, it facilitates specifying models with different parameterizations of the covariance matrix according to different substantive and statistical assumptions (i.e., growth intercepts and slopes can be specified as different or same across latent classes). Fourth, it also allows the inclusion of distal outcomes (not included in the present study) directly in the model to determine if individuals from the different latent trajectories show distinct predictive relations to one or more developmental consequences

(Muthén & Asparouhov, 2009; 2011). Because covariates can influence the classification of the cases, as suggested by Muthén (2004), in the present study, covariates such as school-labeled language status (i.e., EL status) were used in defining appropriate latent class membership.

In the GMM approach, typically, a baseline single-group growth curve model is first identified, which serves as a baseline from which the further exploration of possible unobserved groups proceeds. The intent of the GMM analysis is to obtain a better and more complete representation of the data by allowing for the possibility of multiple unobserved groups (Ram & Grimm, 2009). Once the baseline model is established, three group-difference models that sequentially release the constraints regarding means, covariances, and the pattern of factor loadings are fit. For instance, if examining differences in growth between latent classes of individuals who exhibit higher reading achievement scores versus lower reading achievement scores over time, comparisons would be made as series of competing models examined across the latent classes.

In the baseline (invariance) model, the latent classes are specified to have identical growth patterns, means, variances and covariances, as all parameters are constrained to be equivalent. In this model, all individuals are, in essence, treated as members of a single homogeneous group. In contrast to multiple-group analyses, however, these groups are not *a priori* identified. Instead, the intent is to seek evidence in the data for multiple patterns of student growth that map onto the theoretical expectations (i.e., considerable variability existing among ELs). Figure 2.3 summarizes a basic latent growth mixture model. In principle, a latent categorical variable, C_i, represents the unobserved subpopulation membership for student i, $C_i = 1, 2, \ldots, K$. It refers to a latent trajectory class variable. In Figure 2.3, x represents the time-invariant covariate, y represents the repeated measures of continuous outcomes, both of which are shown as rectangles, signaling they are manifest variables. On the other hand, η_0 and η_1, in the ovals represent the latent growth factors (i.e., level and slope in the preceding section). The pathways suggest that the covariate x influences c and has direct effects on the growth factors η_0 and η_1. Multinomial logistic regression is utilized to identify relatively homogeneous clusters of developmental trajectories (Nagin, 1999). Model parameters are estimated for each class, as is the probability that each individual is a member of each group.

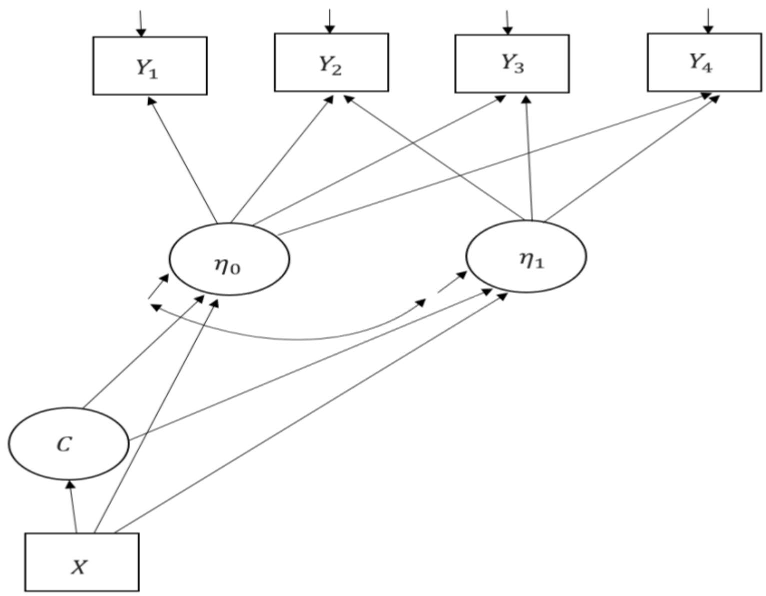

Figure 2-3 Growth mixture model specification

In the current study, GMM is therefore well suited to identify possible heterogeneity in student growth trajectories in the form of emergent latent classes corresponding with their English language status, as well factors in their classroom and school contexts (Muthén & Asparouhov, 2009). Further, this approach readily lends itself to examining the indirect effects of school variables on students' reading growth vis-à-vis their membership in the latent classes, that is, a multinomial logistic regression is utilized to identify relatively homogeneous clusters of developmental trajectories (Nagin, 1999). These individual and group factors can influence reading growth indirectly through their impact on the increasing or decreasing probability of students' membership in the latent growth classes (Muthén & Asparouhov, 2011). Importantly, growth mixture analysis adds the mixture component in the modeling process; thereby allowing one to explore the number of reading trajectories with similar response patterns with regard to EL status. Importantly, GMM allows a flexible way of model specification with respect to means, covariance structures and patterns. If multiple subgroups in longitudinal growth in reading exist, different covariates may be differentially associated with the different latent growth trajectories. In short, GMM is designed such that the technique can empirically assess if the traditional EL category is a single category or contains multiple subgroups that exhibit qualitatively and quantitatively different growth patterns in reading. In addition, it can answer questions regarding whether or not other covariates in the proposed model have indirect effects on students' reading achievement mediated by the latent classes (Muthén & Asparouhov, 2009).

Summary

The theoretical and empirical literature that frames this study provides a way to examine how students' home environments and their school settings influence their longitudinal development in acquiring reading literacy. The steady increase of language minority students in public schools over the past few decades increased the urgency for school districts to provide English language services in order for them to participate fully in public education [Every Student Succeeds Act (ESSA), 2015; Wiley, 2009], as well as stirred debate over their constitutional rights and optimal programs to serve their academic needs (e.g., ESL, bilingual, or mainstream classrooms) since it concerns both issues of equity and excellence. The review of the literature revealed several persistent challenges to further the equitable access of language minority students to services that better meet their diverse language needs.

Previous research indicated students identified as requiring English language services and hence participating in English-oriented programs often receive inferior or incomparable instruction because they had little access to mainstream curricula and native English speakers. The *bioecological model* (e.g., Bronfenbrenner, 2005) and the *integrative model* (Garcia Coll et al., 1996) provide a way to frame the complex problems and processes associated with language minority students' reading development by focusing on the interactions between a series of layered processes comprising individual children, their families, classrooms, and school settings. As Saracho recently noted (2017), the greatest indicator of students' ability to achieve in school is the degree to which they develop in reading and writing. Although individuals' reading and writing capabilities develop throughout their life span, "the period from birth through eight years of age is the furthermost significant period for their literacy development" (p. 302). This is especially critical for language minority students. The research reviewed in this chapter was useful in providing a conceptual background for the measures used in this study to monitor changes in students' literacy development grounded in the empirical literature. Its primary contribution is aimed toward utilizing latent growth modeling to examine the complex relationships embedded within home language backgrounds, classroom instructional environment, and school contexts and processes. Further, utilizing an exploratory analytic approach (growth mixture modeling) facilitates examining the hypothesized underlying heterogeneity present among language minority students in relation to their longitudinal literacy and reading development and school-designated EL status.

Chapter 3 Method

In this chapter, I discuss the study's research design, the data source, analytic samples, and the variables used to answer the proposed research questions. Additionally, I present the mathematical equations to illustrate the latent growth model formulations. Finally, I detail these steps in the analyses with respect to answering the research questions.

Research Design

This study employed a multi-stage analytic approach to address the research questions. I employed latent curve growth analysis via the SEM framework for research questions 1-3. Finally, to address research question 4, I utilized GMM, an exploratory method that focuses on the identification of subgroups of individuals with distinct profiles on a series of indicators. GMM allowed me to explore whether there were different emergent groups of students with respect to their English language proficiency, as prior research noted that labeling students as ELs considerably undermines the heterogeneity existing among children with various linguistic and cultural backgrounds (Han, 2012; Kieffer, 2010, 2012). I next discuss the analytic scheme for each research question.

Research question 1. First, I examined the intra-individual variation in students' overall reading growth measured as IRT theta scores over the seven rounds of data collection. Second, I fit a series of piecewise growth models to identify the one that best described students' growth trajectories, as one or more growth parameters to capture possible different periods of growth during early elementary, later elementary, and middle school (Shanley, 2016). After identifying the model that most closely fit the data in describing reading growth, I used multiple-group SEM to test whether the growth trajectories of four language profile groups were qualitatively or quantitatively different; that is, whether number of growth factors and estimates of growth rates were same or different across the groups.

Research question 2. Building on the previous models, I conceptualized family SES as a formative latent factor (i.e., an underlying construct where the measured variables are considered to be the cause of the factor, for more discussion, see Bollen & Lennox, 1991) using mother's education, father's education, and family income as the causal indicators (Cowen et al., 2012) and examined its impact on the growth trajectories of each language profile group. The second question, therefore, addressed the utility of the family investment model (Conger & Dogan, 2007) by assessing the pathways through which family SES operates, as a direct effect, an indirect effect, or both, on students' reading growth through their home learning environment and literacy practices. I also added other covariates to the model to account for the variability in reading growth, including whether or not the student received English language services (i.e., ESL services), gender, age at school entry, preschool attendance, full day or half-day kindergarten, and first-time kindergarten status.

Research question 3. Han's (2012) multilevel growth analyses indicated at the school level more available ESL instruction was positively related to student reading growth; however, as she noted, the majority of schools with EL children receiving ESL instruction offered these students less than an hour of such instruction daily from kindergarten to grade 3. Moreover, Han (2012) found more classroom ESL instruction did not appear to be particularly helpful for children with non-English backgrounds. Given that the current study also incorporated children's home language spoken with parents and the Oral Language Development Scale or English proficiency test (OLDS)[2] into its definition of children's home language background (and also utilized a longitudinal student sample weight), the third research question examined the effects of specific ESL program features and classroom literacy instruction at the student level, rather than at the school level, with respect to reading growth during students' early school years across groups.

Research question 4. I used EL status to identify possible heterogeneous subpopulations in this portion of the analysis, given its general application in school districts as a means of categorizing language minority students, and I subsequently added classroom and school variables to examine their effects on the probability of belonging to each latent trajectory class. As Research Questions 1-3 suggested, reading trajectories were considerably different for limited English speakers compared with students defined as English Monolinguals, English Dominant Bilinguals, and Mixed Bilinguals (i.e., see Han, 2012). Research Question 4 therefore examined the extent to which school contexts and processes impact the probability of latent class membership at the individual level. Importantly, the latent classes can be considered as the mediator through which school contexts exert indirect effects on students' reading growth trajectories (e.g., Muthén & Asparouhov, 2009).

Data Source

Data were from the National Center for Educational Statistics (NCES) Early Childhood Longitudinal Study, Kindergarten Class of 1998-9 (ECLS-K). It followed a nationally representative sample of 21,409 students from kindergarten to eighth grade drawn from

[2] This measure was used as an English language screening test for children who speak a language other than English at home. It was administered during kindergarten and first grade to measure children's listening comprehension, vocabulary, and command of expressive language (NCES, 2002b). Children who passed this initial assessment were henceforth eligible to take the full English language battery of assessments in the ECLS-K.

approximately 1,400 public and private schools, with approximately 8,700 students (41% of the baseline sample) participating in at least one sampling activity per year across the seven waves of data collection (Tourangeau et al., 2009). Data on student academic and cognitive skills were collected in seven corresponding waves between kindergarten and eighth grade (i.e., 1998-2008), and supporting demographic, instructional, and self-report surveys were also collected from students, parents, teachers, and school administrators (Tourangeau et al., 2009). Assessment data were collected in fall and spring of kindergarten and first grade, and follow-up data collection occurred during spring of third, fifth, and eighth grade.

Sampling scheme. The longitudinal ECLS-K study utilized a multistage probability sampling design, which oversampled particular populations (e.g., Asian and Pacific Islanders) in order to conduct various subgroup analyses. The first sampling stage was based on the four geographic regions in the United States, and the second sampling stage was based on the number of five-year-old kindergarteners enrolled in the private and public schools. Within each stratum, schools were also selected across other characteristics (e.g., urban-rural location, grade configuration). At the third stage, individual children were selected within schools with two independent sampling frames, one representing the oversampling of Asian and Pacific Island students and the other representing other children (Tourangeau et al., 2009).

The original base-year sample for children was representative of all kindergarten children at all schools with kindergarten programs as generated in the ECLK-S three-stage sampling scheme (Tourangeau et al., 2009). The baseline weighted school sample consisted of 866 schools. As the fall first grade sample of children only included approximately 30% of the original kindergarten sample, the number of schools available also represented a stratified sample of the original schools (Tourangeau et al., 2009). More specifically, the school sample utilized in the last set of analyses consisted of 302 of the 866 schools in the weighted kindergarten school sample. This analytic sample closely matched the original school sample based on the original information used to construct the original weighted sample, including census region, urban to rural location, school sector (public, private, private religious), school size, and school structure (i.e., school grade level configurations). School-level weights were not available, however, for this sample (Tourangeau et al., 2009).

Missing data. In one recent K-8 student study examining math achievement and utilizing the ECLS-K data, Shanely (2016) concluded the missing data were most likely missing at random (MAR). She utilized full information maximum likelihood in the analyses, which employs the expected information matrix by default and provides unbiased model estimates for data that are MAR (Muthén & Muthén, 1998-2012). Similar to Shanely, in the longitudinal weighted dataset I utilized, I found the proportion of individuals with complete data at each occasion was near 1.0 (Fall K = .922; Spring K = .951, Fall First = .964; Spring First = .977; Spring Third = .993; Spring Fifth = .985; Spring Eighth = .990). Hence, almost 91% of the children had achievement data at all seven time points (K-8) and almost 92% had complete data for the first five time points (K-3).

Longitudinal sample weight. Statisticians weighted the ECLS-K data to compensate for differential probability of selection at each sampling stage (i.e., under-coverage of the target population) and to adjust for the effects of nonresponse (Tourangeau et al., 2009). After applying the design-effect longitudinal sample weight, the resulting analytic sample consisted of 2,369 cases participating in all seven waves of data collection (i.e., from kindergarten to eighth grade) (Tourangeau et al., 2009). This sample was used to answer the first three research questions. For the last research question, I utilized the final longitudinal, weighted sample of students (N =

4,032) who participated in the first five rounds of data collection (i.e., from kindergarten to third grade). To facilitate the inclusion of school processes, I decided to limit the analysis to the early elementary school years (K-3) because by the end of third grade, almost 28% of students in the study had moved, which increased the number of schools by threefold from the number of schools at the onset of the study. In this weighted sample, over 90% (i.e., N = 3,632) of the students continued in their spring kindergarten school through first grade. I added a student level mobility variable to models to account for its possible effects on achievement growth for students who left their original kindergarten school during first grade (9.9%). An additional 18.7% left their original school between second and third grade (i.e., after the spring first grade assessment); however, this mobility did not enter into the series of growth models as specified, as I parameterized this set of models to focus on the growth occurring during kindergarten and first grade. Of note, this was primarily because there was no direct assessment of growth during students' second grade year, and therefore no information was available on teacher literacy practices in schools during that period.

Variables in the Models

Home language background. Parents in the ECLS-K were surveyed during fall and spring of kindergarten and then again in the spring of first grade regarding the language(s) spoken at home and whether they were primary or secondary. In the current study, children who spoke a language other than English at home were referred to as language minority children, a definition consistent with August and Shanahan (2006) and Kieffer (2010). The importance of using this term is because it acknowledges the heterogeneity existing among immigrant children with regard to both their English language and their home language development. As Kieffer (2010) contended, language minority status is a fixed characteristic that does not change over time, whereas the English language learner (EL) and limited English proficiency (LEP)[3] labels are temporary classifications.

Following this reasoning and an earlier study conducted by Han (2012), I created several categories of children's home language background based on the assessment of English language proficiency (OLDS) and a survey regarding the home language use between parents and the target child (i.e., mother-child dyad language use, father-child dyad language use, and the language use by both parents in talking to the child). Notably, Han (2012) primarily drew on the mother-dyad language use in constructing the language profile groups using the unweighted sample. In the present study, however, I included also father-dyad language usage, both parents' language usage to child in conjunction with the OLDS in defining children's home language background. Notably, there were 122 cases (i.e., 5.1%) with missing values with regard to their language background and hence likely home language category was imputed using mother's education, father's education, reading scores from kindergarten through 8th grade, and their EL status. The imputed values were necessary to facilitate model estimation for the multiple-group analyses as well as ensuring the efficacy of the appropriate longitudinal sample weight. Specifically, these categories and their definitions were as follows:

- English Monolinguals: Child did not need to take an English language screening test or passed the OLDS tests at the fall kindergarten assessment, and the child reported speaking only English to each parent at home, and each parent reported speaking only English to child.

[3] ESSA has replaced this term with EL, as it is less suggestive of stereotypes. However, I will retain this term in the study to refer to children classified in the group with lowest English ability compared to other groups of children.

- English-Dominant Bilinguals: Child did not need to take an English language screening test or passed the OLDS tests at either the fall kindergarten or spring kindergarten assessments. Child reported *sometimes* speaking non-English language to each parent at home, and each parent reported sometimes speaking non-English language at home.
- Mixed Bilinguals: Child did not need to take an English language screening test or passed the OLDS tests at either the fall kindergarten or spring kindergarten assessments. Child reported *often or very often* speaking non-English language to each parent at home, and each parent reported often speaking non-English language at home.
- Limited English Speakers (i.e., Non-English Dominant Bilinguals and Non-English Monolinguals): Child had not passed the language screening test by the beginning of first grade. Child reported very often speaking non-English language to each parent at home, and each parent reported very often speaking a non-English language at home.

In both weighted analytic samples, approximately 77% of children were English Monolinguals, 9.3% were English Dominant Bilinguals, 6.2% were Mixed Bilinguals, and 7.6% were Limited English Proficient. These category percentages were broadly consistent with Han's (2012) unweighted groupings (i.e., 74.96%, 8.50%, 7.91%, and 5.11%). Note that the LEPs in the current study consisted of both Non-English-Dominant and Non-English Monolingual children in Han's (2012) study, hence having a slightly larger proportion likely due to the weighted sample sizes.

Socioeconomic status (SES). SES was a continuous composite initially defined with four indicators: family income, mother's education, father's education, and an occupational prestige score aggregated from mother's job prestige and father's job prestige, ranging from -4.35 to 4.32 (M = -0.2, SD = 1.59). Family income was reported as 13 categories, each consisting of $5,000, with the lowest category being $5,000 or less and the highest category being over $200,000. Parent education was measured as ordinal variables with nine categories, ranging from eighth grade or below to doctorate or professional degree. Mother's and father's occupational prestige was designed to reflect the average of the 1989 General Social Survey (GSS) prestige score. It was a continuous variable, ranging from 0 to 77.5, with a mean of 32.5 (SD = 22.0) for women, and 42.73 (SD = 14.2) for men. Following Han, Lee, and Waldfogel (2012), the occupational prestige scores were divided by 10 for readability. However, in preliminary analyses, none of the prestige indicators was statistically significant in defining the formative latent factor describing family SES, so they were dropped from the final analyses.

Home learning environment. Following Bradley et al. (2001), I defined home learning environment as a composite, given it generally contained cause indicators; that is, the indicators of particular environment dimensions were selected, not because they were assumed to reflect some underlying cause, but because they were presumed to produce a particular effect (see Bollen & Lennox, 1991). In the present study, I selected several items related to parental literacy behaviors collected at kindergarten, first grade, and spring third grade. Specifically, these items included how often the parent read to the child, how often the parent told the child stories, how often the parents shared picture books with the child, how frequently the child read books outside of school, and the estimated number of books at home. The scale on the first four items ranged from 1 = not at all; 2 = once or twice a week; 3 = 3 to 6 times a week; 4 = daily. The number of books at home was recoded to an ordinal indicator as, for kindergarten and first grade, 1 = 30 or fewer books; 2 = 31-55 books; 3 = 56 – 100 books; 4 = over 100 books; for spring 3rd, 1= 50 or fewer books; 2= 51-100 books; 3= 101-200 books; 4= 201-300 books; 5= 300 or more books. The count of the books at home was revised upward at third grade to account for students having more available books as they grew older. Composites for kindergarten ranged from −3.26 to 1.73 (M = −0.09, SD = 0.99), spring 1st ranged from −3.39 to 2.46 (M = −0.08, SD = 1.01), and spring 3rd ranged from −15.1 to 1.16 (M = −0.027, SD = 0.908, see Table 3.1).

Student demographic variables (K-8). As reported by their parents, about 15% of the children in the unweighted analytic sample were of Hispanic origin, 6% were Asian, 14% were Black, 63% were White, and 2% were Other (e.g., Mixed, Native American, Pacific Island). Forty-nine percent of children were males and 51% were females. As shown in Table 3.1, 54.2% of the children attended formal preschools, 91% of the children were first-time preschoolers, and over half of them (50.9%) attended full-day kindergarten. The average age of children upon kindergarten entry was 65.58 months (SD = 4.28). Note that over 92% of the student sample remained at the same school during kindergarten (National Center for Education Statistics, 2001), with increasing numbers of students moving between first and third grades (Tourangeau et al., 2009).

English language services. At the student level, the ECLS-K study included a measure of whether or not language minority children received English language services during the first five rounds of data collection (i.e., kindergarten through third grade, coded 0 = did not receive school language services; 1 = received services of some type). The ECLS–K study contained some information regarding ESL instructional practices offered through the classroom and larger school settings (Han, 2012). As Han (2012) noted, the ECLS-K study defined an ESL program as an instructional program designed to teach English language listening, speaking, reading, and writing skills to EL children and defined a bilingual education program as one in which the student's native language is used to instruct EL children. At the student level, however, it was impossible to distinguish the type of program in which the student participated, so the ESL variable was simply defined as whether or not the student participated in a formal program to assist the acquisition of English literacy. The proportions of students participating in the ESL program are indicated in Table 3.1.

Table 3-1 Weighted descriptive statistics for grades K-8 student background characteristics (n=2,369)

	Wave	n	Mean	SD	Min	Max
Age at entry	Fall K	2,243	65.58	4.28	54.00	79.00
preschool	Fall K	2,348	0.542			
First-time K	Fall K	2,348	0.910			
Full day K	Fall K	2,348	0.509			
ESL	Fall K	2,348	0.249			
ESL	Spring 1st	2,348	0.272			
ESL	Spring 3rd	2,348	0.242			
Home Literacy Practices	Fall K	2,369	-0.085	0.988	-3.260	1.730
Home Literacy Practices	Spring 1st	2,369	-0.080	1.011	-3.390	2.460
Home Literacy Practices	Spring 3rd	2,369	-0.027	0.908	-15.100	1.160
SES	Fall K	1,900	-0.200	1.590	-4.350	4.320

Notes. Sample weight is C1_7SC0.

In Table 3.2, I present the weighted descriptive statistics across the four language profile groups with respect to the key variables included in statistical analyses. Notably, there was a moderate portion of students identified as ELs among English Monolinguals, i.e., 15.2%, 18.2%, and 15.2% at fall kindergarten, spring 1st and 3rd grades, respectively. Mixed Bilinguals and LEPs consistently consisted of larger proportions of ELs at these three time periods. In terms of home literacy practices, LEPs had the lowest composite score during fall kindergarten and spring 1st; however, they seemed to have the highest stimulating literacy environment during 3rd grade compared to students of other language backgrounds. Preliminary tests of mean differences suggested that the differences in home literacy practices were statistically significant ($F_3 = 0.914, p < .05$).

Table 3-2 Weighted descriptive statistics for grades K-8 student background characteristics and reading scores across four language groups (n=2,369)

		English Monolinguals		**English Bilinguals**		**Mixed Bilinguals**		**LEP**	
	Wave	n	Mean	n	Mean	n	Mean	n	Mean
Reading Theta Scores	Fall K	1,804	-1.275 (0.489)	206	-1.230 (0.640)	120	-1.399 (0.481)	53	-1.370 (0.491)
	Spring K	1,816	-0.708 (0.480)	216	-0.688 (0.563)	142	-0.779 (0.506)	79	-0.928 (0.510)
	Fall 1	1,819	-0.482 (0.232)	220	-0.464 (0.564)	146	-0.527 (0.489)	99	-0.725 (0.309)
	Spring 1	1,820	0.125 (0.456)	220	0.131 (0.509)	145	0.055 (0.409)	130	-0.115 (0.431)
	Spring 3	1,811	0.803 (0.308)	219	0.786 (0.355)	144	0.733 (0.276)	178	0.558 (0.338)
	Spring 5	1,811	1.057 (0.292)	220	1.032 (0.272)	145	0.995 (0.274)	179	0.828 (0.281)
	Spring 8	1,802	1.307 (0.140)	219	1.325 (0.355)	146	1.23 (0.315)	179	1.044 (0.352)
Age at entry	Fall K	1,754	65.84 (4.20)	195	65.36 (4.43)	132	64.71 (4.14)	162	63.51 (4.41)
preschool	Fall K	1,875	0.577 (0.909)	195	0.567 (0.058)	117	0.523 (0.071)	181	0.312 (0.049)
First-time K	Fall K	1,875	0.923 (0.476)	195	0.875 (0.031)	117	0.856 (0.037)	181	0.843 (0.039)
Full day K	Fall K	1,875	0.517 (0.909)	195	0.514 (0.058)	117	0.521 (0.072)	181	0.444 (0.058)
ESL	Fall K	1,875	0.152 (0.015)	195	0.458 (0.058)	117	0.514 (0.072)	181	0.858 (0.044)
ESL	Spring 1st	1,875	0.182 (0.016)	195	0.369 (0.053)	117	0.560 (0.073)	181	0.909 0.22
ESL	Spring 3rd	1,875	0.152 (0.014)	195	0.341 (0.052)	117	0.566 (0.071)	181	0.863 (0.043)
Home Literacy Practices	Fall K	1,823	-0.050 (0.023)	220	-0.011 (0.060)	146	-0.262 (0.083)	180	-0.421 (0.098)
Home Literacy Practices	Spring 1st	1,823	0.028 (0.023)	220	-0.234 (0.070)	146	-0.419 (0.090)	180	-0.809 (0.069)
Home Literacy Practices	Spring 3rd	1,823	-0.053 (0.022)	220	-0.026 (0.049)	146	0.024 (0.095)	180	0.204 (0.046)
SES	Fall K	1,457	0.06 (1.46)	176	-0.41 (1.60)	116	-0.71 (1.69)	151	-2.20 (1.10)

Other classroom ESL-related variables. Teacher surveys provided some additional classroom information including the allocation of time to key English-language services within their classrooms, availability of language aides, and the type of program as either in-class or pullout. These variables were measured during kindergarten and first grade. These ESL classroom characteristics included hours per day allocated to ESL-related activities (i.e., "1-30 minutes," "31-60 minutes," "61-90 minutes," and "more than 90 minutes")[4], hours per day a paid ESL aide was available in the classroom (i.e., "0 hours or no aide" to "2 or more hours"), and whether children received either pull-out or in-class ESL instruction. Approximately 9.7% of the kindergarteners and 6% of the first graders had an ESL aide. For kindergarteners, the distribution of EL children having an English aide was 82.8% (0 hour/day), 2.7% (1 hour/day), 1.3% (2 hours per day), and 1.2% (3-6 hours/day). For first graders, the distribution of EL children having an English aide was 67.4% (0 hour/day), 3.7% (1 hour/day), 0.8 % (1-2 hours per day), and 0.5% (more than 2 hours per day). In addition, the percentage of EL children who received in-class ESL service was about 10% and 8% at kindergarten and first grade, respectively. The percentage of EL children who received pull-out ESL service was about 9% and 11% at kindergarten and first grade, respectively.

Teacher instructional time. This composite variable examined the frequency teachers reported providing instruction in various literacy areas during the year including pre-reading and reading skills (e.g., letter names and sounds, working on phonics, working with printed material, reading out loud, choosing books) and oral and written communication (e.g., writing the alphabet, learning new vocabulary, and using language experience writing activities). Individual items were recoded such that 0 = never; 1 = once per month or less, 2 = 2-3 times per month; 3 =

[4] Measurement on ESL-related activities in first grade was not used in the analyses as it only contained 93 individuals (2.3%) of the analytical sample (*n* =4,032) and they came from teacher file.

1-2 times per week; 4 = 3-4 times per week; 5 = daily. The first grade composite score added the frequency of choosing books to read and having silent reading during class. In preliminary analyses, I found there was no statistically significant difference in teacher coverage of pre-reading and reading skills for students receiving or not receiving EL services during kindergarten ($r = .00$, $p > .05$, not tabled); however, for first grade, EL students were significantly more likely to be assigned to teachers who did not spend as much time on the identified set of pre-reading and reading skills ($r = -0.47$, $p < .01$, not tabled). Additionally, items pertaining to phonics had greater weight, such as working on letter names, writing alphabet, and working on phonics.

School contexts and processes. These school characteristics were collected at the spring of kindergarten from school administrator reports. Of the 302 schools in the analytic sample, 55% offered some sort of ESL or bilingual programs. Of the 167 schools offering ESL/Bilingual programs, 7.8% offered such programs for less than 1 year, 9% for 1 year, 25.1% for 2 years, 29.3% for 3 years, 19.2% for 4 years, 8.4% for 5 years, and 1.2% for 6 years. Less than half of the schools (i.e. 46.6%) were Title I schools, and about half of the schools had small percentages of LEP students (i.e., less than 3%). Further, I created several composite scores to capture school processes and resources, guided by variables found in previous school effectiveness research to boost students' academic outcomes. Specifically, I constructed a composite score to indicate the level of school services available for EL students (M =1.227, SD =1.668), which consists of six items: (1) whether there are translators for LEPs; (2) whether there is written translation for LEPs; (3) whether there are home visits to LEP families; (4) whether there is outreach worker help with enrollment; (5) whether there is non-English parent meetings; and (6) whether there are any other LEP services. Similarly, I constructed a composite score indicating schools' improvement process to describe the administrator's perceptions of the school's relative success in improving six areas of school academics (increasing students' language and number skills, raising test performance, helping low achievers, staff development, being open to new ideas and methods) during the last three years (M = 2.50; SD = 1.60).

I also constructed two composite scores representing teachers' preparation and teaching experiences. Teacher preparation was the factor-weighted sum of five items concerning teachers' educational background: (1) reading courses, (2) child development courses, (3) early education courses, (4) elementary education courses, and (5) highest education level. The composite measure of teaching experience was the factor-weighted sum of four items: (1) years taught kindergarten, (2) years taught first grade, (3) years taught Grades 2-5, and (4) years taught at present school. Both variables were standardized in the analysis with mean of 0 and standard deviation of 1.

English reading achievement. Children's overall reading achievement was the outcome of interest. The achievement scores come from adaptive exams in reading which were fielded by NCES during each wave of data collection. The exam was adaptive in that, based on answers to a few items, children were then offered a test form which matched their cognitive and ability level. To monitor student achievement progress, all test forms from kindergarten through eighth grade were calibrated on the same scale, in order for the scores to be longitudinally comparable. In order to achieve this end, ECLS-K used Item Response Theory (IRT) as detailed in Lord (1980)[5]. In the current study, theta scores were preferred to scaled scores because (1) the theta scores were potentially less determined by choices made in test item selection; and (2) they represented the distribution of reading ability on a vertical equated scale that was roughly bell-shaped, which better matches the assumptions underlying statistical modeling. In addition, as argued, the

[5] See the technical appendix for more information on the assessment methods and Item Response theory in the ECLS-K manual (Rock & Pollack, 2005).

standard deviation of theta scores remained fairly stable compared to the scale scores, which lends itself to comparing learning growth rates similar to effect sizes (Logerfo, Nicols, & Reardon, 2006). In other words, theta score lends itself to comparison of learning by the same students across time and comparisons of students at different levels at the same time point. Logerfo et al. also emphasized that theta scores should not be interpreted as a measure of inborn or genetic capacity but as a learned ability to score well on a particular battery of tests. Furthermore, as reading theta scores were used as the single indicators in the latent growth models, they provided assurance that the same construct was assessed by each manifest variable score because the IRT model supports this inference (Widaman et al., 2010).

Time metric. A key concern for longitudinal data analysis is to select the appropriate time metric to capture the amount of growth taking place over time. I chose wave instead of age as the time scale for two primary reasons: (1) it uses fewer degrees of freedom, as it allows the time loadings to be freely estimated as opposed to imposing a polynomial term to capture the nonlinearity of the growth trajectories typically done in a multilevel modeling approach (Curran & Hussong, 2003); (2) it eases the computational burden by generating a single residual covariance matrix, as all individuals share the same time scores rather than having a unique value at each time point should age be employed (Singer & Willet, 2003). Additionally, since the focal interest of the study was to understand the learning processes taking place during kindergarten year and first grade with respect to an array of classroom literacy practices, I adopted the waves approach and therefore coded time in a manner that provided a detailed snapshot or summary of the growth process at these two critical junctures. Table 3.3 presents the correlations between reading theta scores for students who shared the same assessment schedule (i.e., wave). As shown, reading scores were much stronger correlated between two successive rounds and then weakened over time (i.e., ranging from 0.882 to 0.569).

Table 3-3 Intercorrelations between reading theta scores from kindergarten through grade 8 (n =2,369)

Theta scores	**Fall K**	**Spring K**	**Fall 1st**	**Spring 1st**	**Spring 3rd**	**Spring 5th**	**Spring 8th**
Fall Kindergarten	–						
Spring Kindergarten	0.801	–					
Fall 1st	0.787	0.882	–				
Spring 1st	0.678	0.781	0.830	–			
Spring 3rd	0.625	0.689	0.715	0.767	–		
Spring 5th	0.594	0.660	0.663	0.735	0.846	–	
Spring 8th	0.569	0.579	0.610	0.636	0.746	0.803	–
M	-1.278	-0.717	-0.493	0.109	0.780	1.034	1.284
SD	0.503	0.491	0.495	0.462	0.321	0.295	0.375

Data Analysis

Overall, to answer the research questions I conducted the analyses in four basic steps. The first part focused on specifying students' latent growth trajectories over the period (K-8) of the study. After identifying the best-fitting model in describing reading growth, I employed multiple-group SEM to examine its fit across the language background groups (research question 1). The second part extended the growth models across students' home literacy and SES backgrounds to examine how background influence student growth (i.e. research question 2). In the third part, I examined the effects of specific ESL program features and classroom literacy instruction across groups at the student level, rather than at the school level, with respect to students' reading growth primarily during their early school years (research question 3). The last part utilized GMM to identify homogenous subgroups of students who may have similar background, classroom, and school characteristics in ways that help explain student growth during their K-3 years (research question 4). Identifying such groups can be challenging, however, given that student data exist in large heterogeneous samples that vary across students, schools, and time (Bowers & Sprott, 2012). These analyses were performed using Stata 15 and Mplus 8.0.

Specifying Student Reading Trajectories

Modeling intra-individual change. I first defined a series of measurement models using the seven repeated IRT reading scores at each occasion to estimate the optimal number of growth parameters (see Eq. 3.1-3.2). Then, I compared the nested models using *Satorra-Bentler* scaled chi-square difference tests (*TRd*; 2001) because the analyses were conducted using robust maximum likelihood estimation and a scaling factor was generated for all chi-square values. Following the SEM framework, the repeated measurements on y over T time points (i.e., the number of panel waves) is represented by a multivariate outcome vector of reading theta scores $(y_{i1}, y_{i2}, \ldots, y_{iT})'$ for individual i:

$$y_{it} = \nu_t + \Lambda_t \eta_i + \varepsilon_{it}, \qquad \varepsilon_{it} \sim N(0, \sigma^2) \tag{3.1}$$

where ν is a $t \times 1$ vector of repeated-measure intercepts (which is fixed to 0), Λ is the $t \times q$ matrix of factor loadings (i.e., time-related loadings) on the latent growth factors specified to capture the reading growth trajectory, η is a $q \times 1$ vector of latent factors where q is the number of these factors, and ε is a $t \times 1$ vector of time-specific measurement errors. Importantly, latent curve growth analysis allows for great flexibility in the specification of the error covariance structure and is not restricted to classical assumptions of independence and homoscedasticity (Willet & Keiley, 2000). It is assumed that the latent growth factors and measurement errors are independent and multivariate normally distributed. Following Shanley (2016), who examined growth in math, several different latent growth models were examined consisting of one or more growth periods to capture student reading growth during their K-8 school years. The final model consisted of three distinct growth periods beginning at fall kindergarten, fall first grade, and spring 3rd grade. Hence, Equation 3.1 can be expressed in the matrix terms to specify a latent curve model with three distinct periods (see Figure 3.1) as follows:

$$\begin{bmatrix} y_{i1} \\ y_{i2} \\ y_{i3} \\ y_{i4} \\ y_{i5} \\ y_{i6} \\ y_{i7} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 1 & 1.6 & 0 & 0 \\ 1 & 1.6 & 1 & 0 \\ 1 & 1.6 & 2.1 & 0 \\ 1 & 1.6 & 2.1 & * \\ 1 & 1.6 & 2.1 & 1 \end{bmatrix} \begin{bmatrix} \eta_{0i} \\ \eta_{1i} \\ \eta_{2i} \\ \eta_{3i} \end{bmatrix} + \begin{bmatrix} \varepsilon_{i1} \\ \varepsilon_{i2} \\ \varepsilon_{i3} \\ \varepsilon_{i4} \\ \varepsilon_{i5} \\ \varepsilon_{i6} \\ \varepsilon_{i7} \end{bmatrix}, \qquad (3.2)$$

where the reading IRT achievement scores spanning kindergarten to grade eight are represented by four latent variables, η_{0i}, η_{1i}, η_{2i}, and η_{3i}, denoting initial status at fall kindergarten and three growth slope factors, respectively. Specifically, the first column of the Λ matrix sets the loadings of initial status to 1s to capture the starting point of the development growth trajectory at time 1. Correspondingly, the elements in the remaining columns are used to capture the curvature in reading growth during three distinct periods (Meredith & Tisak, 1990), as learning theory suggests that each child's true trajectory is non-linear and follows an "S-shaped" trajectory that smoothly traverses the region between a lower asymptote and an upper asymptote (Feuerstein, 1979, 2002). The model is summarized visually in Figure 3.1, where the dotted arrows are shown to indicate parameters that are fixed to 0 as summarized in Equation 3.2.

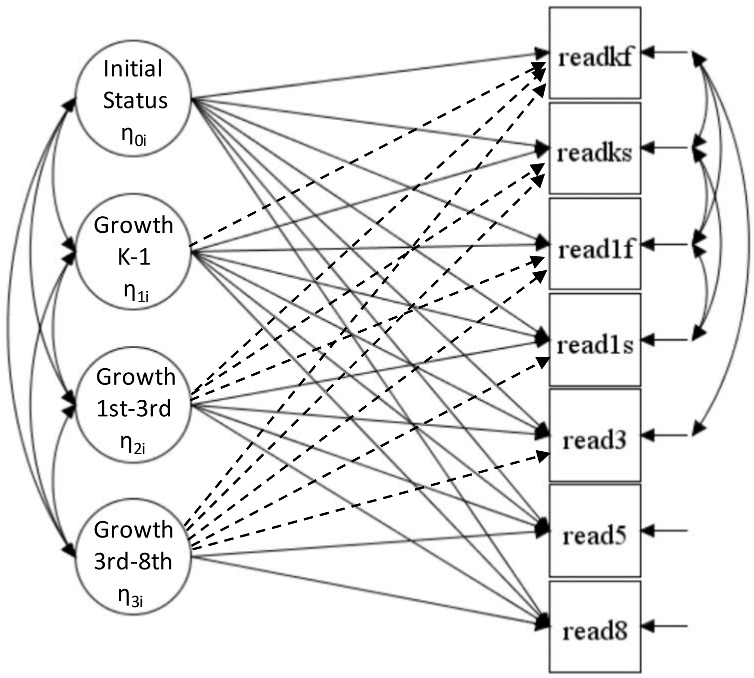

Figure 3-1 Single-level piecewise latent growth model for K-8 reading achievement.

Modeling inter-individual change. The inter-individual differences of change in the growth parameters can be modeled by assuming that each student draws his or her latent growth vector from a multivariate normal distribution (Willet & Keiley, 2000) as follows in Equation 3.3:

$$\begin{bmatrix}\eta_{0i}\\ \eta_{1i}\\ \eta_{2i}\\ \eta_{3i}\end{bmatrix} \sim N\left(\begin{bmatrix}\mu_{\eta 0}\\ \mu_{\eta 1}\\ \mu_{\eta 2}\\ \mu_{\eta 3}\end{bmatrix}, \begin{bmatrix}\sigma^2_{\eta 0} & \sigma^2_{\eta 0\eta 1} & \sigma^2_{\eta 0\eta 2} & \sigma^2_{\eta 0\eta 3}\\ \sigma^2_{\eta 1\eta 0} & \sigma^2_{\eta 1} & \sigma^2_{\eta 1\eta 2} & \sigma^2_{\eta 1\eta 3}\\ \sigma^2_{\eta 2\eta 0} & \sigma^2_{\eta 2\eta 1} & \sigma^2_{\eta 2} & \sigma^2_{\eta 2\eta 3}\\ \sigma^2_{\eta 3\eta 0} & \sigma^2_{\eta 3\eta 1} & \sigma^2_{\eta 3\eta 2} & \sigma^2_{\eta 3}\end{bmatrix}\right). \qquad (3.3)$$

Conceptually, as this equation suggests, each student draws a different value for her intercept and slope means from the same underlying distribution, so each can possess a unique growth trajectory. There are four mean parameters, $\mu_{\eta 1}$, $\mu_{\eta 2}$, $\mu_{\eta 3}$, and $\mu_{\eta 4}$, describing the average population intercept and slopes at three time periods. Further, the four variance parameters, $\sigma^2_{\eta 0}$, $\sigma^2_{\eta 1}$, $\sigma^2_{\eta 2}$ and $\sigma^2_{\eta 3}$, summarize population inter-individual differences in initial true reading achievement score and true rate of change in reading achievement. The covariance parameters represent the population association between initial status and growth rates as well as among the growth rates themselves. The distribution of the individual growth parameters in Equation 3.3 can be modeled with a set of individual-level covariates as follows:

$$\eta_i = \mu_\eta + \mathrm{B}X_i + \zeta_i, \qquad \zeta_i \sim N\ (0, T_\zeta) \qquad (3.4)$$

where μ_η is a vector of initial status and growth intercepts, B is a matrix of regression coefficients of the exogenous *X*s predicting the growth factors, and ζ_i are residuals that contain the partial variances and covariances of true intercept and slopes, controlling for the effects of the predictors of individual change. Importantly, Equations 3.1-3.4 assume that all individuals are drawn from the same population. The means of the latent growth factors, $\mu_{\eta 0}$, $\mu_{\eta 1}, \mu_{\eta 2}$, and $\mu_{\eta 3}$, show the average development of measurement across seven panel waves within a homogenous population.

Examining student trajectories across language groups. Once the baseline growth model of best utility was identified, I next fit it to four language profile groups to assess the adequacy of model fit based on several common model fit criteria. These included the comparative fit index (CFI), standardized root mean square (SRMR), and Root-Mean-Square-Error-of-Approximation (RMSEA). I specified a series of multiple-group latent growth models to test several hypotheses regarding the equality of factor loadings, equality of factor variances and covariances, and the equality of factor means (Duncan et al., 2013). I next added home literacy practices and family socioeconomic status in the latent growth model as covariates to examine research question 2. Specifically, I conducted structural invariance analyses to examine whether the model relationships differ across groups. If the baseline and constrained models are not significantly different, one can conclude that the structural parameters examined are invariant between the groups. In contrast, if the baseline and constrained models are significantly different, one can infer that there is a moderating effect on the causal relationships proposed in the model, and this effect varies by group. In other words, group membership is thought to moderate this relationship (Sass & Schmitt, 2013).

Past literature defines structural invariance in numerous ways. In general, the approach has the benefit of testing a number of statistical assumptions and research questions within a single modeling framework (Sass & Schmitt, 2013). Structural invariance tests can be important, because although inter-factor covariance might be invariant, after adjusting for other variables in the model, predictive relationships between these variables might not be invariant (Sass & Schmitt, 2013). Specifically, these successive structural invariance tests included (1) constraining the covariances among the mediators (i.e., home literacy measures) to be equal, (2) constraining the structural paths from the mediators to the growth outcomes to be equal across the four groups, (3) constraining the structural paths from SES to each of the growth outcomes to be equal, and (4) constraining the structural paths from SES to the mediators to be equal. This approach facilitates examining the pathways relating family SES, home literacy practices, and students' reading growth across the four language profile groups within the framework of multiple-group SEM analysis, controlling for child characteristics (see Muthén & Muthén, 1998-2012).

The multiple-group analyses were performed to address: (1) measurement and structural invariance among four language profile groups with respect to the equality of factor loadings, equality of variances and covariances, and equality of factor means; (2) moderation analyses with respect to whether the structural relationships between family socioeconomic status, home literacy practices, and growth outcomes were the same. Following this logic, I first tested whether the language profile groups differed on the means, variances, and covariance of the growth latent variables through a series of nested models. For individual *i* at time *t*, the basic latent growth model in Equation 3.1 can be extended across *j* groups (*j* = 1,2,…,*J*):

$$y_{itj} = \upsilon_t + \Lambda_{tj}\eta_i + \varepsilon_{itj} \qquad \varepsilon_{itj} \sim N\ (\varepsilon_{itj} \sim N(0, \sigma^2) \qquad (3.5)$$

$$\Sigma_j = \Lambda_j \Psi_j \Lambda_j{}' + \Theta_j \qquad (3.6)$$

where $\upsilon_t$is a vector of time related measurement intercepts (fixed to 0 for all groups)[6], Λ_{tj} is a matrix of time-related factor loadings defining the latent factors (η), and ε_{itj} is a vector of time-related errors, assumed to be normally distributed, with zero means, and residuals contained in Θ_j. The multiple group specification facilitates the specification of separate factor loadings, factor variances and covariances (contained in Ψ_j), and errors across groups. The key parameters are the time-related factor loadings (Λ_t), factor variances and covariances (Ψ_j), and latent growth factor means (μ_η). One challenge, however, is a situation where there might not be measurement invariance across all of the groups (i.e., some of the factor loading equalities may not hold for all groups). If measurement invariance (or partial measurement invariance) holds well enough, however, I can proceed to investigate differences in factor latent means and perhaps structural relations between key predictors and the measurement model.

Moderation analyses. A structural model as in Equation 3.4 can then be added to examine differences in the effects of covariates on the latent growth factors between the groups:

[6] Scalar invariance was assumed in this analyses.

$$\eta_{ij} = \mu_j + \mathrm{B}_j X_{ij} + \zeta_{ij}, \qquad \zeta_{ig} \sim N\ (0, \Psi_j) \qquad (3.7)$$

where there are *j* groups (*j* =1,…,*J*), μ_j is a group-specific vector of latent growth intercepts, $\mathrm{B}_j$is a matrix of regression coefficients relating a set of covariates (X_i) to latent factors within each group, and the residual vector ζ_{ij} is assumed to be unrelated to other variables and normally distributed with means of zero and covariance matrix Ψ_j(Muthén & Muthén, 1998-2012). I reported unstandardized estimates for examining structural invariance and standardized estimates for assessing the relative impacts of covariates (Sass & Schmitt, 2013).

The next set of multiple-group analyses focused on adding classroom variables with respect to the ESL program features and classroom reading instructional practices. In particular, interaction terms between ESL services and teachers' allocation on reading instruction were of interest, as they test hypotheses regarding whether or not the targeted literacy skills during kindergarten and first grade mitigate the negative effects associated with EL status. The model is summarized in Figure 3.2. The rectangular box surrounding latent growth model implies each of the four language background groups can have its own growth model with covariates that may exert differential effects within each of the groups.

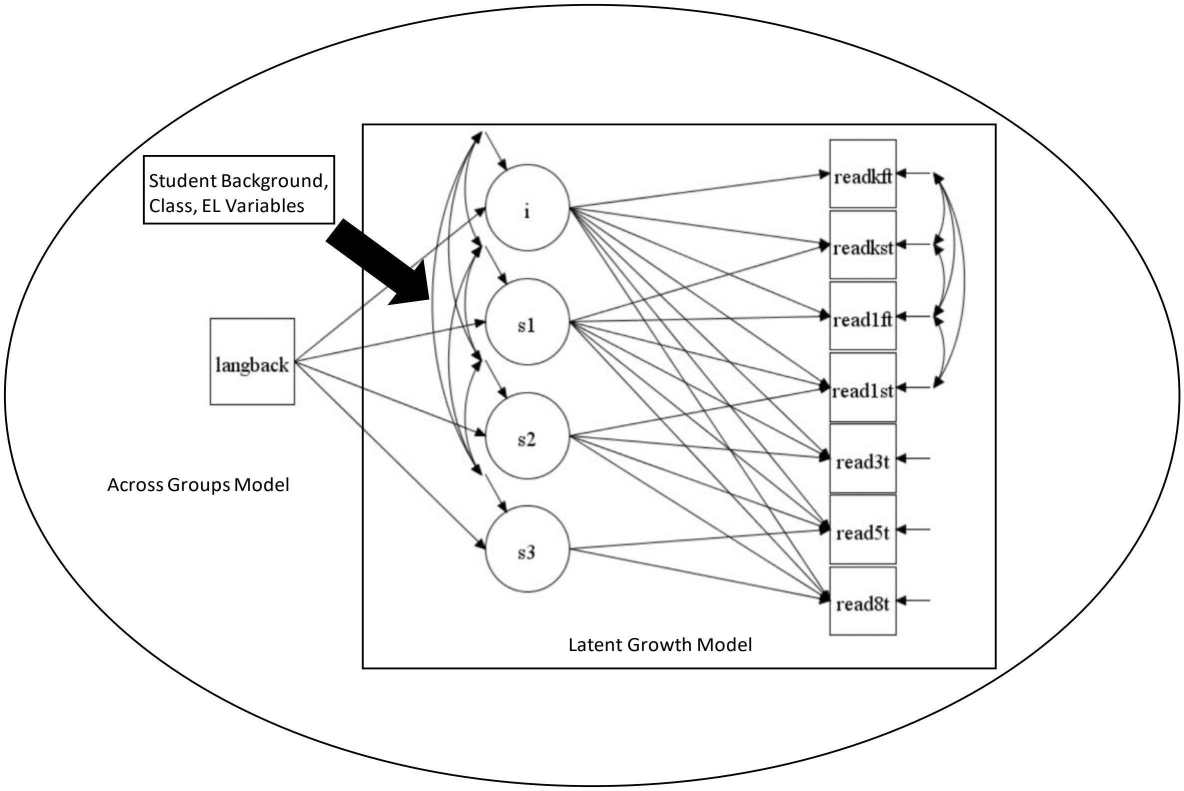

Figure 3-2 Proposed model examining the impact of student background, teacher, and EL program features across language background groups.

Growth mixture model (GMM). GMM allows for the identification of empirically defined homogenous subgroups in large heterogeneous datasets while testing for the associated effects of a selection of variables at multiple levels within the model (Bowers & Sprott, 2012). Growth mixture models have two basic parts: the latent growth model as specified in Equations 3.1-3.4, which defines individuals' latent initial status and latent growth rates over one or more periods of the study; and the latent class model, which is to understand and predict individual differences (or variability) in parameters reflecting participants' growth in outcomes over time. The goal of the second part of the model, which is specified as a multinomial logistic regression model, is to assign individuals to latent classes based upon similar patterns of data by inferring each individual's highest probability of class membership (Berlin, Parra, & Williams, 2014).

In this study, the reading scores were nested within students, and then students' reading growth trajectories were nested within several latent trajectory classes, the exact number of which emerged through several steps in the GMM analysis. In this approach, latent classes were added to the model one by one, and the fit of each additional class added was assessed against the previous *n*-class model. If multiple latent growth classes in reading exist, a set of covariates may be differentially associated with each emergent latent trajectory class. Initially, I proposed a baseline model with measurement invariance across the latent classes (i.e., equal means, equal variances covariances, and equal factor loadings). Specifically, I specified the time loadings in the Λ vector in the same manner as indicated in Equation 3.2, and a detailed examination of the output showed there was no negative variances or correlations greater than 1. Then, the 2-$Class_{means}$ model where the groups were allowed to differ with respect to the mean change function was carried out (e.g., $\mu_{\eta1}, \mu_{\eta2}, and\ \ \mu_{\eta3},$ see Eq. 3.3).

The next model 2-$Class_{means+covs}$ additionally allowed the extent of interindividual differences differ among groups. In addition to the means, the variances and covariances of the intercept and slope factors may differ (e.g., $\sigma^2_{\eta1\eta0}, \sigma^2_{\eta2\eta1}, and\ \sigma^2_{\eta3\eta2}$, see Equation3.3). The next model, 2-$Class_{means+covs+pattern}$, was specified to allow for differences in the shapes or patterns of change (e.g., groups with different factor loadings). Here, the elements of Λ vector were estimated separately for the groups. This final relaxation of the model enabled the groups to have completely different shapes or patterns of change. For the three-class models, the same steps were carried out. One proceeds in similar fashion until it becomes obvious that further classes do not improve the fit of the model to the data. In this case, I found the four-class model did not fit the data, since there were no individuals assigned to the fourth specified latent class.

After establishing the growth trajectory model with optimal number of latent classes, a series of covariates can be added to the model to explain formation of the latent trajectory classes:

$$logit[P(C_{ik} = 1)] = \alpha_k + \sum_{q=1}^{Q} B_{qk} X_{qi} \qquad (3.8)$$

where C_{ik}=1 if individual *i* belongs to class *k* and is zero otherwise, *C*=1, 2, 3, .., *k*, and *k* is the total number of mixture components of latent class given the observed covariate X_{qi}. The *k* intercepts for the latent classes in multinomial regression model are defined in a separate alpha vector for the emergent latent classes (*C*). There can be *k* – 1 intercepts because the last one is standardized to zero for model identification (Muthén & Asparouhov, 2009). In the present study, the first covariate added was students' EL status. Note, therefore, that B_{qk} is the increase in the log odds of being in class *k* versus the reference group for a unit increase in X_{qx}. In this case, the coefficient is interpreted as the increase in log odds of belonging a particular latent class versus the reference group when comparing EL versus non-EL students. I then added a set of covariates to the model based on their theoretical relevance and compatibility with other variables in the predictive model. Following Asparouhov (2006), because there were only longitudinal child-level sample weights available for these data, I conducted a single-level analysis. Asparaouhov recommends not including a single-level design weight within a multilevel model, as this strategy is likely to bias the resulting estimates. Moreover, because the mixture portion of the model was specified at the student level, the latent factors of the group-level model cannot be affected by a within-group categorical latent variable *C* (L. Muthén, 2018). The proposed model is summarized in Figure 3.3.

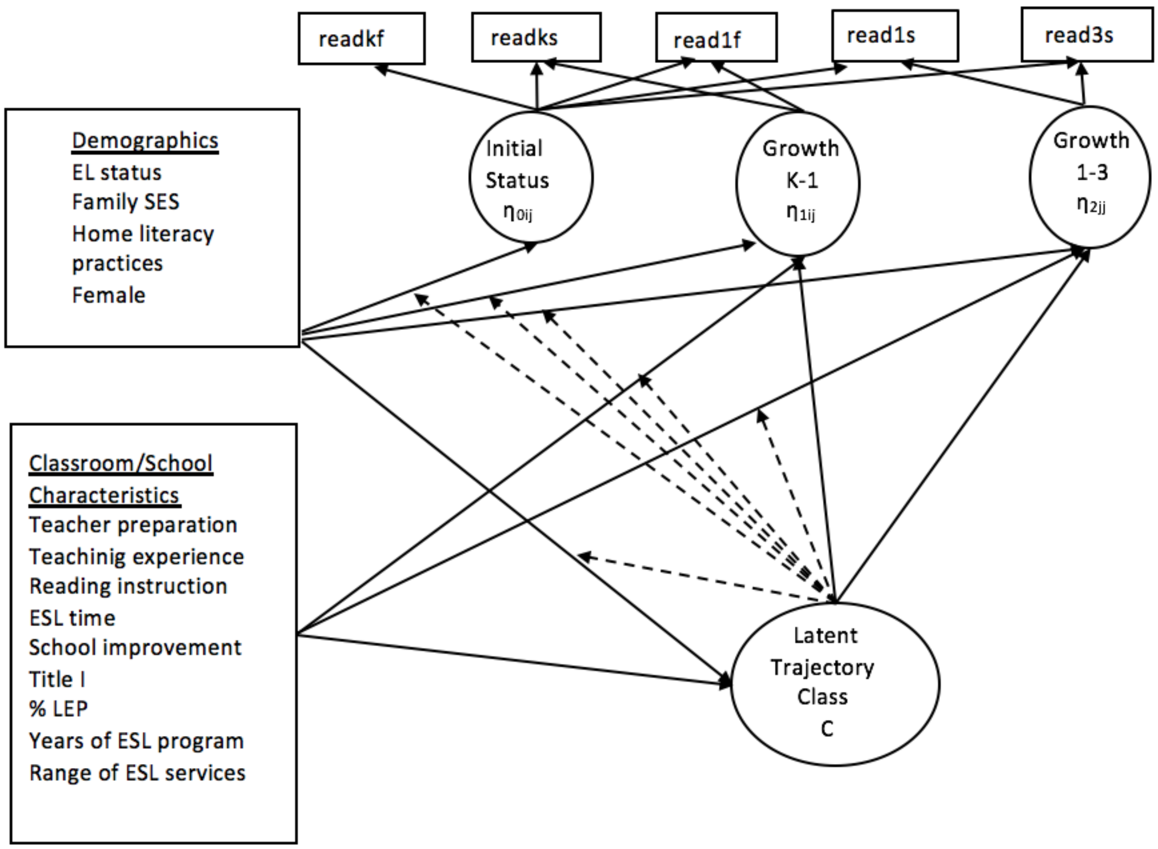

Figure 3-3 Growth mixture model for the simultaneous estimation of latent trajectory classes using reading achievement scores from fall kindergarten to spring 3rd grade.

Examining Model Fit

Model fit in SEM is based on failing to reject the null hypothesis—that is, one wishes to fail to reject the null hypothesis, which allows the analyst to conclude that the proposed model is consistent with the data. Often several fit criteria are used to evaluate the suitability of a proposed model. The most commonly used fit index is the chi-square statistic. The chi-square coefficient is defined as the minimum value of the discrepancy function *F* and is equal to $\chi^2/(N-1)$. When the significance level is below $p = .05$, it suggests rejecting the null hypothesis that the model is a plausible representation of the data. It is important to note, however, that the chi-square coefficient is inflated by sample size (Bentler & Bonnet, 1980).

In contrast to the “exact” test provided by the chi-square statistic, the Root-Mean-Square-Error-Of-Approximation (RMSEA) provides a “close” test of model fit, since it measures the discrepancy per degree of freedom in the proposed model (Marcoulides & Hershberger, 1997). This makes the test a bit more lenient than the chi-square test in evaluating the suitability of a particular model. The test also includes a confidence interval around the RMSEA estimate. RMSEA will often provide a reasonable statistical test of model fit (defined as a one-sided test of the hypothesis that the RMSEA ≤ 0.05) in situations where the chi-square coefficient would lead to rejecting the proposed model as a plausible fit to the data. The benefit is that RMSEA provides a statistical test on which to base failing to reject or rejecting the null hypothesis. The Comparative Fit Index (CFI) is scaled from 0 to 1 and compares a preferred model to a baseline or null model. In general, a CFI of 0.95 or above is indicative of an adequate model fit (Hu & Bentler, 1999). The standardized Root Mean Residual (SRMR) provides an overall summary of the magnitude of the residuals in the model. In most situations, an SRMR coefficient of 0.08 or less indicates a good-fitting model (Hu & Bentler, 1999).

Choosing the optimal number of latent classes is a key consideration in GMM, which should be informed by theory, past findings, and a variety of statistical fit indices (Bauer & Curran, 2003; Lubke & Muthén, 2005; Ram & Grimm, 2009). Conventional chi-square based fit indices noted above in SEM analyses (e.g., CFI, RMSEA, etc) are unavailable in mixture modeling (see McLachlan & Peel, 2000, for details). Instead, models can be compared using relative fit information criteria such as the Bayesian Information Criteria (BIC), Akaike Information Criteria (AIC), and adjusted BIC. Lower values on these information criteria indicate better-fitting models (Nylund, Asparouhov, & Muthén, 2007). Further, models can be evaluated with respect to the accuracy or the confidence with which individuals are classified as belonging to one group or another. Entropy, a statistic that ranges from 0.00 to 1.00 (as implemented in Mplus), is an increasingly used summary indicator of the conditional probabilities of individuals' group membership (Jedidi, Ramaswamy, & Desarbo, 1993). High value of entropy (>.80) indicate that individuals are classified with confidence (i.e., the model is generally certain that individuals belong to a particular class) and there is adequate separation between the latent classes (see Muthén, 2004). When selecting models with similar fit indices (e.g., BIC), a higher value of entropy is favored.

Finally, comparisons can be made on an array of likelihood ratio tests included in the Mplus output that quantify specific comparisons between the model of interest and a model with one fewer class. The tests include Vuong-Lo-Mendell-Rubin likelihood ratio test (VLMR-LRT) and Adjusted Lo-Mendell-Rubin likelihood ratio test (Adjusted LRT), and they apply a corrected likelihood-ratio distribution (a chi-square distribution is inappropriate) to compare a model with C against $C-1$ unobserved groups (see Lo, Mendell, & Rubin, 2001; Muthén, 2004). A significant (p <.05) VLMR-LRT or Adjusted LRT test indicates the model with $C-1$ classes should be rejected in favor of the model with C classes. These tests can be supplemented with bootstrapping procedures that are interpreted in the same manner, but generate and use empirical distributions of the likelihoods (see Muthén & Muthén, 1998-2012). Note that the likelihood ratio tests compare models that differ only in the number of classes. Thus, they can be used to select among models that only differ with respect to the number of classes but are not appropriate for comparing models that allow for different types of between-class differences.

Chapter 4 Results

This chapter presents the results of the study organized with respect to the four guiding research questions. Preliminary tests of model assumptions suggested that the repeated reading theta scores utilized in this study were robust to the assumption of normality without severe kurtosis or skew (i.e., kurtosis ranged from -0.220 to 1.121 and skewness ranged from -.793 to .605). Pearson correlation revealed statistically significant correlations between all reading achievement scores ranging from .083 to .882, and an inspection of a random selection of 25 sample reading achievement trajectories (see Figure 4.1) suggested the presence of multiple growth periods spanning kindergarten through grade 8.

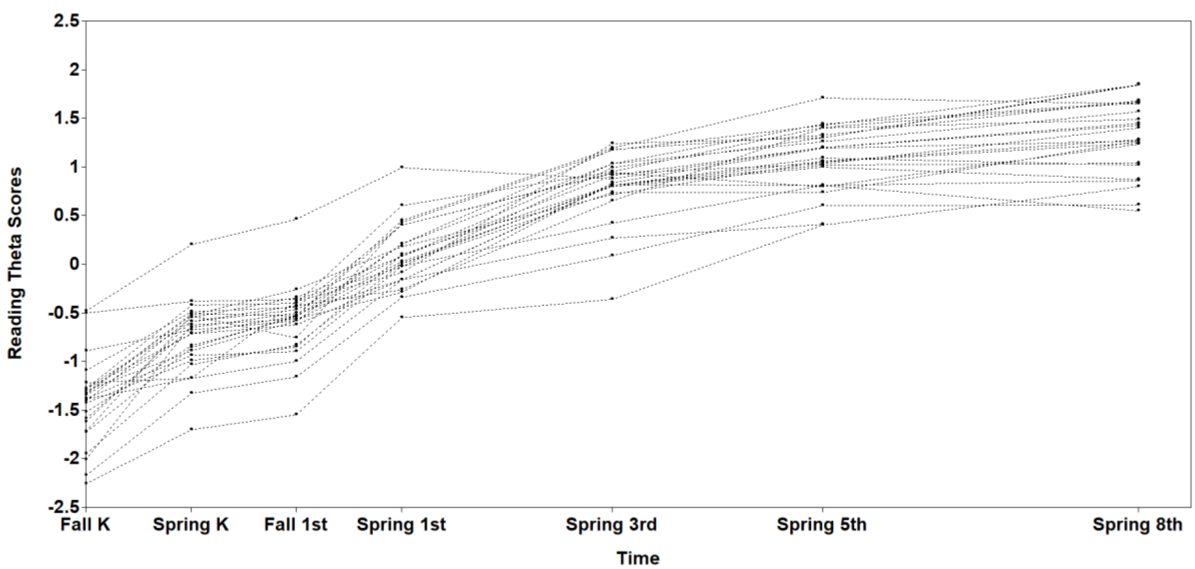

Figure 4-1 Random sample of 25 actual K-8 reading achievement growth trajectories.

Research Question1a: What Is the Overall Shape of Reading Trajectories from Kindergarten through Grade 8?

Although over a short period of time a linear model will often be sufficient to examine individual growth, the example growth trajectories in Figure 4.1 suggest the presence of nonlinearity. When an exploratory examination suggests the presence of nonlinearity, one option is to break up the nonlinear trajectories into separate linear growth components, an approach that is attractive where for substantive reasons the researcher wishes to examine growth during separate periods (Raudenbush & Bryk, 2002). I fit a series of preliminary latent growth models to examine this research question in more detail. Models 1-3 in Table 4.1summarize the goodness-of-fit of unconditional models with one, two, and three latent growth periods (i.e., growth slope factors) respectively. Specifically, following Shanley (2016), the third piecewise model was specified to examine student growth occurring during the kindergarten academic year (fall K through spring K), the first grade academic year (fall 1st through spring 1st), and the mid-late elementary academic years (spring 3rd through spring 5th). The key assumption of Model 3 was that the first two observations (e.g., fall K and spring K) within each growth period were parameterized to be are linear, consistent with the findings from Fitzpatrick, Grissmer, and Hastedt (2011). The third occasion within each period was first freely estimated (i.e., spring K to fall 1st) to allow for any nonlinearity occurring within each period.

I examined the relative fit of each proposed model to the data by examining several model fit indices (as described in Chapter 3). Table 4.1 shows that Model 3 was the best fitting model according to several common model fit criteria (CFI = .987, SRMR= .050, RMSEA = .049, p > .05). More specifically, Model 1 (one growth period) had the largest RMSEA coefficient (0.060) with significant p-value (0.046), which suggests it could be rejected on statistical grounds. Models 2 and 3 had non-significant RMSEA coefficients (p > .05), but with Model 3 being favored over Model 2, given its stronger supportive criteria such as higher CFI coefficient and lower SRMR and Adjusted BIC coefficients.

Table 4-1 Model fit indices for grades K-8 reading achievement unconditional models, unstandardized latent growth parameter estimates, and variance estimates

	M1: one slope		**M2: two slopes**		**M3: three slopes**	
Means	Estimate	S.E	Estimate	S.E	Estimate	S.E
Initial status (I)	-1.037***	0.021	-1.307***	0.019	-1.306***	0.019
Growth 1 (S1)	0.570***	0.015	0.569***	0.009	0.569***	0.009
Growth 2 (S2)			0.606***	0.010	0.601***	0.006
Growth 3 (S3)					0.501***	0.009
Variances						
Initial Status (I)	0.162***	0.003	0.144***	0.016	0.161***	0.017
Growth 1 (S1)	0.003**	0.001	0.050**	0.008	0.044***	0.011
Growth 2 (S2)			0.008***	0.002	0.003*	0.002
Growth 3 (S3)					0.015**	0.005
Covariances						
I with S1	-0.015**	0.005	-0.024	0.134	-0.032	0.009
I with S2			-0.007		-0.009	0.007
I with S3					0.003	0.007
S1 with S2			-0.015**	0.101	-0.007*	0.004
S2 with S3					0.003	0.002
S1 with S3					-0.011**	0.004
Fit Indices						
Chi square	114.257		80.510		67.360	
Df	12		11		10	
p value	0.000		0.000		0.000	
RMSEA	0.060		0.052		0.049	
p value	0.046		0.377		0.522	
CFI	0.977		0.984		0.987	
SRMR	0.069		0.063		0.050	
Adjusted BIC	1432.088		1337.110		1293.684	

Notes. Standard errors in parentheses. ***$p<.01$ **$p<.05$ *$p<.10$

Furthermore, because the analyses described here were conducted using robust maximum likelihood estimation, a scaling factor was generated for all chi-square values, and I conducted Satorra-Bentler scaled chi-square difference tests (*TRd*; 2001) when comparing nested models (i.e., where one model can be obtained by fixing one or more parameters from an alternative model). Nested model comparisons in Table 4.2 suggested that Model 2 demonstrated a statistically-significant improvement in model fit Model 1 ($Trd_{(2)}$= 38.043, p < .001), and Model 3 provided a statistically stronger fit to the data than Model 2 ($Trd_{(1)}$= 11.460, p < .001). I also examined several hypotheses regarding variance and mean structures (not tabled). These tests suggested latent variances associated with slope factors were non-invariant over time. Additionally, model fit significantly decayed when constraining the intercepts to be equal over time (i.e., the chi-square coefficient increased by over 1600 with a difference of 3 degrees of freedom). After identifying the model of best utility (M3), I retained this slope parameterization for future models.

Table 4-2 Model comparisons with one, two, and three slope parameters

	No. Parameters	Scaling Factor	LL	base	Δ No. parameters	Δ-2LL	*cd*	*Trd*	*P* value
M1	23	3.918	-663.229						
M2	25	3.814	-613.431	M1	2	99.596	2.618	38.043	<.001
M3	26	3.842	-587.407	M2	1	52.048	4.542	11.460	<.001

Given that Model 3 provided the strongest fit to the data compared to the models with one and two growth periods, respectively, it is appropriate to examine the parameter estimates in Table 4.1 more closely for that model. For Model 3, the three estimated sample growth means were statistically significant (p <. 05). The estimated growth unstandardized coefficients suggested that the incremental learning occurred at a slightly higher rate during first grade than in kindergarten (β =.601 and β = .569, respectively) and then demonstrated a reduced growth rate during late elementary school years (β =.501). In addition, Model 3 revealed that there was a small negative covariance between the mean of slope one and the mean of slope three ($\sigma = -.011, p < .05$). Further, the variances associated with each latent growth factors in Model 3 were statistically significant, indicating that there was considerable variability in children's initial reading achievement and learning growth rates during the three time periods. Note that there was considerable variability at kindergarten entry, which then diminished somewhat during kindergarten, and during first grade, the variability approximated zero, suggesting initial evidence of a school equalizing effect taking place during students' early elementary years (Quinn, Cooc, McIntyre, & Gomez, 2016). In contrast, during grade 3 to grade 5, more variability appeared, given the extended time period.

Research Question1b: What Are the Quantitative Differences in Reading Growth across the Four Language Background Groups?

Fitting Model 3 (M3) across four language background groups separately. The second part of Research Question 1 examined whether the student growth trajectories varied across four identified home language groups. A preliminary step in examining the invariance of a proposed model across groups is often to estimate the same model across each group separately (Byrne, Shavelson, & Muthén, 1989). I fit the model with three growth slope parameters (Model 3) to each language background group and examined the relative fit of each model to the data separately. Table 4.3 summarizes the model fit information for each group. As shown, Model 3 demonstrated relatively good fit in each of the four groups, albeit with the English Monolingual group having the largest chi-square value ($\chi^2 = 52.354, p < .05$). This was not surprising given its large sample size (n =1,820). Of note, the relative measure of fit indices associated with each group was nonsignificant (RMSEA, $p > .05$), which suggests Model 3 should not be rejected on statistical grounds alone for any group, and SRMR remained less or equal to .08, often used as the cut-off boundary for a good fitting model (Hu & Bentler, 1999). The initial results therefore suggested that the proposed model was consistent with the data for each group separately.[7]

Table 4-3 Grades K-8 reading achievement growth model Fit for each language group

	N	Chi Square	Df	*p*	RMSEA	*p*	CFI	SRMR	ABIC
M3a: English Monolinguals	1822	52.354	12	.000	.043	.819	.989	.048	611.327
M3b: English Bilinguals	220	17.310	12	.138	.045	.271	.991	.083	357.387
M3c: Mixed Bilinguals	146	14.656	12	.261	.039	.559	.995	.057	72.984
M3d: LEP	180	25.168	12	.014	.078	.128	.972	.081	162.373

Testing hypotheses regarding equal variances and covariances and equal latent growth means across groups. After determining the models fit adequately across each group separately, a second step is to determine whether a proposed model fits in a similar way across the groups by testing a series of more restrictive hypotheses related to its metric and structural equivalence. As Sass and Schmitt (2013) noted, although metric and scalar invariance are required to examine differences in latent factor means, they are also required to test for equality of covariance between latent factors and for structural invariance. Table 4.4 summarizes the model fit indices for the successive nested models which further examined measurement (M4) and structural invariance across the groups (M5-M10). Preliminary analyses (not tabled) indicated that the model with no constraints (i.e., with freely estimated variances and covariances across groups) did not converge, which often happens with unequal group sample sizes (Kim,

[7] Preliminary growth models were also examined by race/ethnicity. These models were not as salient in defining differences in reading growth as home language background, with the exception that students of Hispanic origin had significantly lower reading test scores than their Caucasian peers at kindergarten entry.

Mun, & Smith, 2014). As Table 4.4 indicates, Model 4 was the best fitting and, therefore, chosen as the baseline model. Model 4 had invariant factors and factor loadings for all three growth periods across groups and utilized the IRT theta scores, which provided evidence of measurement invariance (Sass & Schmitt, 2013). Models 5-10 examined hypotheses regarding structural invariance across groups. Structural invariance refers to tests regarding whether or not covariance structures, latent means, and structural coefficients (e.g., path coefficients between covariates and latent factors) may be equal across groups (Sass & Schmitt, 2013). Covariance invariance refers to whether the unstandardized relationships between latent factors are equal across groups, while structural invariance analyses test whether the unstandardized path relationships between latent variables, or between covariates and latent variables, are equal across groups. Thus, researchers can also test the invariance of the structural coefficients to ensure that the theoretical model generalizes across different groups (Sass & Schmitt, 2013). The fit of each successive model in Table 4.4 was evaluated against the baseline model (Model 4), once again using Satorra-Bentler (2001) scaled chi-square difference test (*TRd*).

Model 4 demonstrated considerable preliminary measurement invariance, with invariant intercept and growth slope variances for kindergarten (slope 1) and third-eighth grade (slope 3), and partial invariance for slope 2, with variances constrained to one fixed value for English Monolinguals and English Bilinguals and a second fixed value for Mixed Bilinguals and LEPs. The latter parameters were fixed to slightly different values to facilitate model convergence. In addition, covariances between growth slopes were also invariant across groups, as were covariances between intercepts and growth slopes (i.e., with the covariances between the intercept and slope 1 and between the intercept and Slope 2 fixed to be equal and invariant across groups).

Table 4-4 Grades K-8 reading achievement growth model fit for measurement invariance

	Chi-square	No. Para	Scaling Factor	LL	base	Δ No. para	Δ-2LL	*Trd*	*P* value
M4: equal loadings, intercept, S1, S3 variance and covariance[a]	138.917	78	2.93	-440.284					
M5: equal variance and covariance (except EM)[b]	149.015	76	2.91	-455.517	M4	2	30.466	8.256	<.05
M6: equal slope means	161.374	69	3.03	-464.687	M4	9	48.806	22.561	<.01
M7: equal s3 means	140.352	75	2.95	-441.979	M4	3	3.39	1.395	>.05
M8: equal s2 means	148.390	72	2.97	-452.474	M7	3	20.99	8.500	<.05
M9: equal s1 means	153.193	72	3.01	-455.150	M7	3	26.342	17.445	<.01
M10: equal intercepts	156.083	72	2.98	-461.994	M7	3	40.03	17.951	<.01

Notes. [a]Model 4 had partial invariance for slope 2 variances and invariant covariances between intercept and growth slopes and between growth slopes across groups.
[b]Model 5 has two more invariant parameters in the psi matrix.

Model 5 with two more invariance parameters demonstrated a significant decay in model fit, $Trd_{(2)} = 8.23, p < .05$, and was therefore rejected. Next, successive models were compared with equal slope means (Model 6-Model 10). These results suggested that Model 7 with equal slope 3 means was the best model, as indicated by the Santora-Bentler chi-square difference test, $Trd_{(3)} = 1.40, p > .05$. Hence, the slope 3 means were constrained equal across groups for future models. These results suggested that the reading growth rates were significantly different for each language background group during kindergarten and first grade whereas the growth rates during the last time period were constant for all four groups.

Examining reading growth rates across groups. After establishing there was considerable evidence of measurement invariance and preliminary evidence of structural invariance for Model 7, Table 4.5 summarizes the unstandardized estimates for the average initial status and growth rates for each group. I reported unstandardized estimates for the measurement invariance analyses (Sass & Schmitt, 2013), as well as for calculating effect sizes (LeGerfo, Nichols, & Reardon, 2004), which facilitate the examination of student learning rates over time and across groups. The effect sizes provide an indication of standardized learning gaps between groups. Following LeGerfo et al., I constructed the effect sizes by dividing the mean growth rates by the standard deviation at the base period to construct a measure of growth in standard deviation units. Specifically, I first estimated the standard deviation at the beginning of each growth period (e.g., at the beginning of the kindergarten) to compute the effect sizes for gains during kindergarten and then followed this same procedure to compute the effect sizes for gains during first grade and at spring third grade to compute the effect size for gains during the last period. I obtained these estimates by shifting the intercept of the latent growth model to that point in time, which does not change the slope estimates, but did change the estimated intercepts (i.e., initial status means). Notably, recoding time did not alter or change the fundamental growth process observed in the model with the intercept at kindergarten entry. By recoding time, I simply reorganized, or reparameterized, the same information to compute effect sizes that could be used to examine differences in growth between the groups over the period of the study. Note that results of the effect size and theta score gains are similar because theta scores are already approximately normal, so renormalizing by dividing by the standard deviation had little impact.

Table 4-5 Weighted unstandardized growth estimates for four language background groups (Model 7 growth3 means constrained equal)

	English Monolinguals	English Bilinguals	Mixed Bilinguals	LEP
Growth Means	Estimates	Estimates	Estimates	Estimates
Initial Status (K)	-1.277* (0.021)	-1.215* (0.084)	-1.454* (0.057)	-1.591* (0.082)
Growth 1	0.568* (0.010)	0.541* (0.033)	0.667* (0.022)	0.503* (0.060)
Growth 2	0.598* (0.007)	0.587* (0.019)	0.584* (0.021)	0.675* (0.026)
Growth 3	0.502* (0.009)	0.502* (0.009)	0.502* (0.009)	0.502* (0.009)
Growth Variances				
Initial Status (K)	0.143* (0.016)	0.143* (0.016)	0.143* (0.016)	0.143* (0.016)
Initial Status (1st)[a]	0.126* (0.016)	0.168* (0.057)	0.138* (0.029)	0.208* (0.070)
Initial Status (3rd)[b]	0.086* (0.009)	0.086* (0.028)	0.074* (0.012)	0.086* (0.027)
Growth 1	0.025* (0.004)	0.025* (0.004)	0.025* (0.004)	0.025* (0.004)
Growth 2	0.004 (0.001)	0.004 (0.001)	0.004 (0.001)	0.004 (0.001)
Growth 3	0.015* (0.004)	0.015* (0.004)	0.015* (0.004)	0.015* (0.004)
Covariances				
I with S1	-0.015* (0.004)	-0.015* (0.004)	-0.015* (0.004)	-0.015* (0.004)
I with S2	-0.015* (0.004)	-0.015* (0.004))	-0.015* (0.004))	-0.015* (0.004))
I with S3	0.003 (0.007)	0.003 (0.007)	0.003 (0.007)	0.003 (0.007)
S1 with S2	-0.004 (0.003)	-0.004 (0.003)	-0.004 (0.003)	-0.004 (0.003)
S1 with S3	-0.009* (0.003)	-0.009* (0.003)	-0.009* (0.003)	-0.009* (0.003)
S2 with S3	0.003 (0.002)	0.003 (0.002)	0.003 (0.002)	0.003 (0.002)

*Notes. Standard errors are in parentheses. *p < .05*
[a] *estimated by re-parameterizing the model.*

Figure 4.2 illustrates the reading growth trajectories across home language backgrounds in an effect size (i.e., standard deviation) metric. As shown, the reading growth rates for English Monolinguals and English Bilinguals were very similar. In contrast, students in the Mixed Bilingual group at kindergarten entry were somewhat lower in English language skills than students in the previous two groups. For example, at kindergarten entry, the average discrepancy between Mixed Bilinguals and English Monolinguals was 0.46 standard deviation (see Appendix A to examine the effect sizes). During kindergarten, however, Mixed Bilinguals grew at a greater rate than English Monolinguals (i.e., the average discrepancy was 0.26 standard deviation), as indicated by the steeper slope between fall K and spring K. From that point, their growth rates were consistent with the English Monolingual group (i.e., 0.04 standard deviation difference in growth during first grade). In contrast, LEPs appeared to lag considerably behind the other groups throughout the study. Notably, however, they grew at a greater rate than English Monolinguals, English Bilinguals, and Mixed Bilinguals during the first grade (i.e., with average discrepancy of 0.21 standard deviation, 0.22 standard deviation, and 0.25 standard deviation, respectively), providing initial evidence for the effectiveness of classroom practices implemented during first grade, as the traditional curriculum often entails teaching of basic literacy skills, such as phonics.

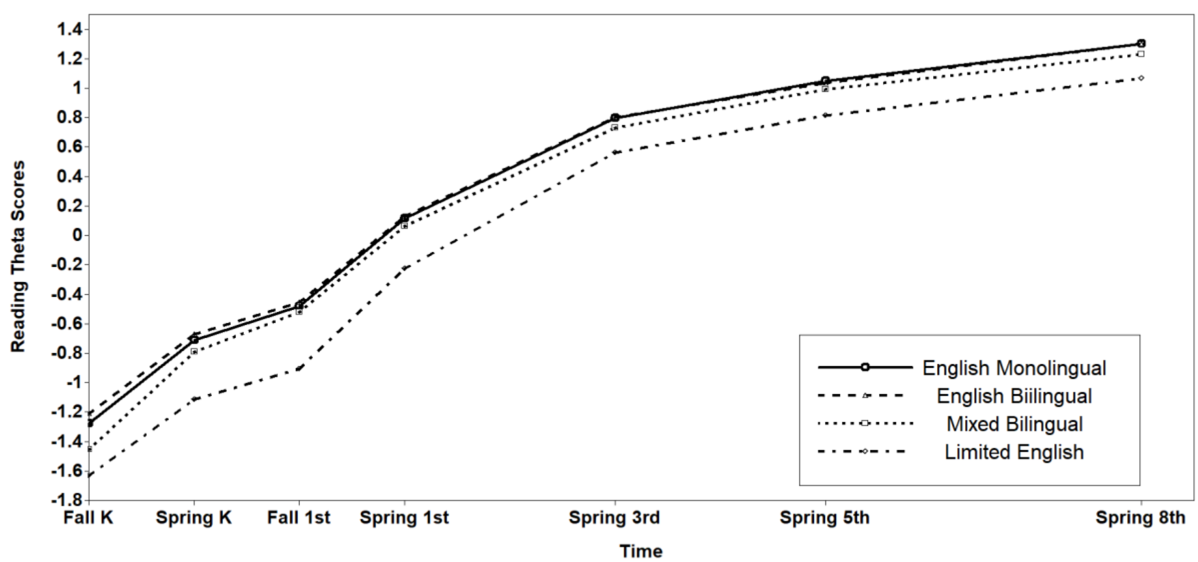

Figure 4-2 Sample means and estimated means for K-8 reading achievement growth across the four language profile groups.

Research Question 2: How Do Family SES and Home Literacy Practices Interact with Language Background to Influence Reading Growth?

After establishing that the latent growth models with equal covariance structures and equal slope 3 means fit across the four groups, the second research question focused on how family SES background and home literacy practices might affect growth trajectories within the four groups. This part of the analyses examined whether there was any evidence of structural differences (i.e., the strength of the relationships among the covariates and latent growth factors) across four language profile groups. As a first step, I estimated a base model in which all model parameters were freely estimated (i.e., no constraints among family SES, home literacy practices, and growth factors). Subsequently, successive models (M11a-M11d) represented more restrictive and nested models within this larger base model—that is, forcing specified relationships to be equivalent across groups. Comparison of the fit of the more constrained to the less constrained model indicates the degree to which the two models are significantly different from each other, and whether the former is a worse-fitting model of the data structure than the latter. Indication of a worse-fitting model is suggestive that the more restrictive model does not fit the data as well as the less restrictive model and, as such, that there are meaningful differences across the groups in terms of the pattern of associations among the sets of covariance matrices.

Results of this moderation analysis in Table 4.6 indicated the strength of the structural pathways between mediators (i.e., home literacy practices) and growth factors (Model 11b) did not differ significantly across the language background groups (*Trd* = 14.72, $p > .05$). In contrast, however, the pathways from SES to growth outcomes (Model 11c) and to home literacy practices (Model 11d) provided strong evidence of structural non-invariance (i.e., *Trd* = 31.21, $p < .05$; $Trd = 14.72, p < .05$, respectively).

Table 4-6 Moderation results: Effects of language background on model relationships

Constrained Paths	X^2(d.f.)	*Trd*	*P* value	CFI	RMSEA
M11: none	432.975			0.976	0.040
M11a: constraining covariances of literacy practices	454.974	21.34	<.05	0.974	0.040
M11b: constraining literacy practices -> growth factors	447.998	14.72	>.05	0.975	0.039
M11c: constraining SES -> growth factors	477.394	31.21	<.05	0.973	0.040
M11d: constraining SES -> literacy practices	531.036	14.72	<.05	0.967	0.044

As a result, Model 11b with equal pathways from home literacy practices to growth outcomes was retained as the final model which yielded satisfactory model-fit indices ($\chi^2 =$ 1071.876, p < .05, RMSEA= 0.043, p > .05, CFI=0.945, SRMR=0.054). In particular, the RMSEA test suggested the model should not be rejected on statistical grounds alone. This model adequately represented change in reading scores over time with the addition of covariates of interest.

For convenience in summarizing the results, I present Figures 4.3a-4.3d to illuminate the different patterns that emerged across the four language groups with regard to family SES and home literacy practices, with the dotted lines indicating non-significant paths. Note that I reported the standardized coefficients in the figures to facilitate understanding the relative impacts of covariates in each group, whereas I used the unstandardized estimates to conduct the structural invariance analyses. First, Figures 4.3a-4.3d suggest that mother's education, father's education, and family income were all robust indicators of family SES. Specifically, mother's education seemed to matter more for children speaking limited English (LEPs) compared to children of other language backgrounds. Second, family literacy practices was shown to be statistically significant only at the beginning of kindergarten regardless of children's language background, suggesting the presence of differing levels of home learning environments as early as kindergarten years. This finding may also reflect the fact that young children's early literacy competence and experiences are largely associated with maternal characteristics.

Of central interest to Research Question 2 are the pathways from family SES to literacy practices and reading growth outcomes, which I found to vary across children with different language backgrounds. The direct effects of SES on initial status and growth each period are summarized in the figures, and the remaining relationships (i.e., direct effects of SES on growth one and two as well as indirect relationships) are presented in Table 4.7. From these figures, the associations between SES and home literacy practices were found to be robust during the last time period (i.e., between spring grade 3- spring grade 5) irrespective of children's language backgrounds, while during students' kindergarten years, this relationship was statistically significant only for English Monolinguals and Mixed Bilinguals. In addition, no significant association was found for LEP students. Clearly, the robustness of the relationship was most pronounced among English Monolinguals, suggesting the pervasiveness and dominance of the SES-literacy mechanism among mainstream English-speaking families.

Further, in examining the figures and standardized estimates reported in Table 4.7, SES principally affected reading growth directly; that is, only two indirect paths through home literacy practices were significant at $p < .05$ for English Monolinguals and Mixed Bilinguals, both at kindergarten entry (see Table 4.7). Notably, upon kindergarten entry, there was some evidence that family SES influenced reading performance primarily through home literacy practices [see Figure 4.3c for Mixed Bilinguals ($\beta = .042, p < .10$)], and for English Monolinguals, both direct and indirect effects of SES were statistically significant. In other words, the mediating effect of home literacy practices was salient for these two groups at the beginning of the study. However, such mediating effects were nonetheless non-existent during the subsequent growth periods. In part, this may cast into question the validity of the parent interview items that were available to capture the degree to which children were exposed to a literacy-stimulating home environment.

Residual variances unexplained for each latent growth factor in Figures 4.3a-4.3d also indicated the salience of family SES in explaining reading growth across language profile groups. For example, SES-literacy-reading growth accounted for relatively larger proportions of the variances at kindergarten entry for English Monolinguals and English Bilinguals (R^2 = .37 and R^2 =.31, respectively) than for Mixed Bilinguals and LEPs (R^2 = .03 and R^2 = .18, respectively). Further, The SES paths consistently explained more variance during earlier growth periods (i.e., kindergarten and first grade) across these four language profile groups, suggesting that the relatively larger impact of family SES on children’s reading achievement and growth in early grades.

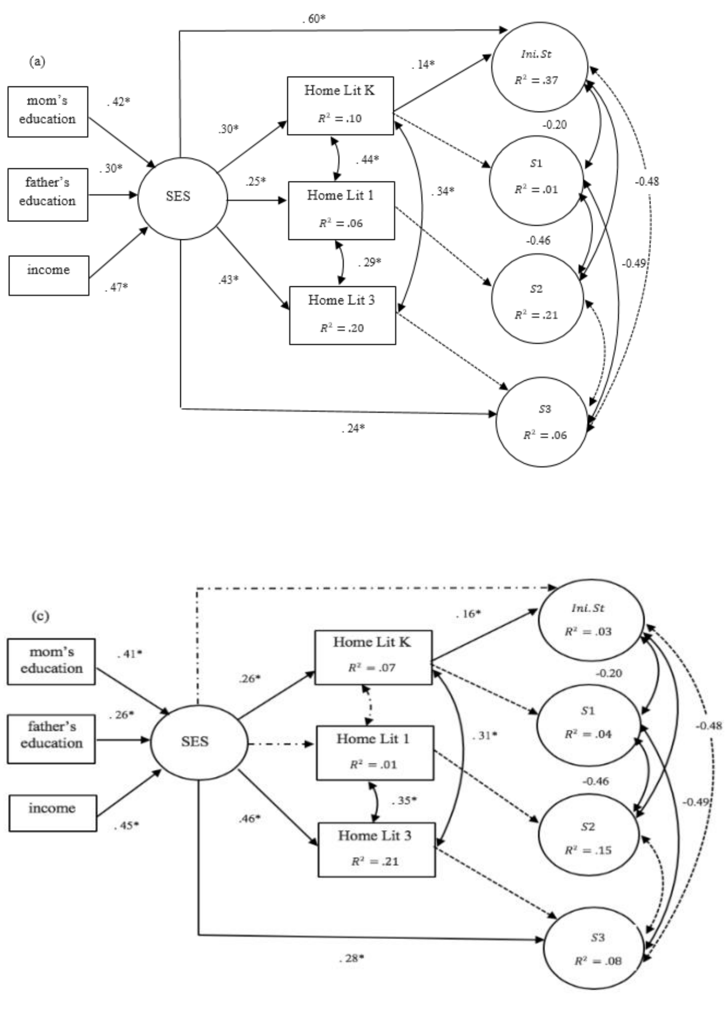

Figure 4-3 Path diagrams for English Monolinguals (a), English Bilinguals (b), Mixed Bilinguals (c), and LEPs (d). Shown coefficients are standardized path coefficients.

Table 4-7 Standardized estimates for moderation analyses with covariates in Model 11b

	English Monolinguals		English Bilinguals		Mixed Bilinguals		LEP	
	Estimate	S.E	Estimate	S.E	Estimate	S.E	Estimate	S.E
Initial Status	-4.912***	0.296	-4.049***	0.537	-4.565***	0.592	-5.464***	0.510
Age at entry	0.032	0.039	-0.018	0.116	-0.192	0.167	-0.139	0.123
All day K	-0.042	0.026	-0.082	0.056	0.132	0.110	0.210***	0.078
Female	0.093**	0.046	-0.188	0.186	0.060	0.198	-0.198	0.172
Literacy	0.126***	0.041	0.117***	0.040	0.161***	0.052	0.150***	0.049
Preschool	-0.037	0.027	0.060	0.072	-0.013	0.120	0.053	0.071
Repeat K	-0.006	0.025	-0.038	0.098	0.054	0.128	0.265*	0.161
SES	0.560***	0.045	0.506***	0.108	0.081	0.204	0.355***	0.121
Growth 1	3.800***	0.359	3.335***	0.574	4.183***	0.469	2.205***	0.701
ESLK	0.046	0.043	0.238**	0.109	0.158	0.116	0.016	0.087
Female	0.042	0.066	0.026	0.197	0.168	0.147	0.642***	0.140
Literacy K	-0.050	0.058	-0.044	0.052	-0.049	0.058	-0.041	0.048
SES	-0.033	0.067	-0.043	0.148	-0.168	0.148	-0.147	0.167
Growth 2	9.641***	0.226	8.263***	1.063	5.971***	0.987	6.959***	0.949
ESL1	-0.019	0.055	-0.283**	0.135	-0.129	0.094	0.021	0.130
Female	-0.134	0.087	0.344*	0.204	-0.263	0.177	-0.564***	0.190
Literacy1	0.048	0.049	0.047	0.047	0.037	0.037	0.034	0.035
SES	-0.470***	0.076	-0.395**	0.178	0.339*	0.183	0.060	0.155
Growth 3	3.508***	0.550	3.418***	0.601	3.370***	0.533	3.341***	0.540
ESL3	-0.075	0.062	-0.027	0.200	0.230	0.147	-0.030	0.142
Female	-0.053	0.081	0.307	0.308	-0.259*	0.148	0.380*	0.197
Literacy3	0.035	0.074	0.036	0.077	0.038	0.080	0.032	0.068
SES	0.247***	0.093	0.204	0.156	0.280**	0.136	0.112	0.173
Literacy K	-0.788***	0.118	-0.211	0.197	-0.753***	0.284	-0.482**	0.246
Literacy K on SES	0.297***	0.038	0.092	0.073	0.260**	0.112	0.049	0.114
Literacy 1	-0.586***	0.119	-0.420	0.311	-0.396	0.312	-0.540***	0.197

Table 4.7 (continued)

	English Monolinguals		English Bilinguals		Mixed Bilinguals		LEP	
	Estimate	S.E	Estimate	S.E	Estimate	S.E	Estimate	S.E
Literacy 1 on SES	0.245***	0.041	0.072	0.119	0.077	0.117	0.070	0.084
Literacy 3	-1.047***	0.098	-1.043***	0.251	-1.258***	0.227	-1.488***	0.171
Literacy 3 on SES	0.433***	0.030	0.376***	0.104	0.459***	0.092	0.338***	0.084
Indirect Effect of SES								
SES-lit-Initial Status	0.038***	0.013	0.011	0.009	0.042*	0.024	0.007	0.017
SES-lit-Growth1	-0.015	0.017	-0.004	0.006	-0.013	0.016	-0.002	0.005
SES-lit-Growth2	0.012	0.012	0.003	0.007	0.003	0.005	0.002	0.004
SES-lit-Growth3	0.015	0.032	0.014	0.029	0.017	0.037	0.011	0.023

Notes. ***p<.01 **p<.05 *p<.10 Chi square = 1071.876, CFI = 0.945, RMSEA= 0.043 (p > .05), SRMR= 0.054

Research Question 3: To What Extent Do Classroom Instruction Practices and ESL Programs Contribute to Reading Growth from Kindergarten through Grade 3 with Respect to Language Background?

Building on the previous model (Model 11 with invariant literacy parameters and variant SES parameters), the next analyses examined how several ESL program features and teacher variables might influence the progress of individual children. Specifically, Model 12 added variables including the amount of time students received ESL services per day, the types of ESL services (i.e., pull-out or in-class), as well as teachers' allocation of instructional time targeting key literacy domains during kindergarten and first grade. The purpose was to examine the extent to which particular classroom practices and language service features might be associated with students' reading growth across the four language background groups. Preliminary analyses suggested that the parameters associated with reading instruction during kindergarten could be constrained to be equal across the groups without resulting in a significant decay in model fit indices (note that it was not significant in any of the groups).

Results are summarized in Table 4.8. During the first growth period (i.e., kindergarten), receiving ESL services was positively associated with reading growth among mixed bilinguals ($\beta = 0.774, p < .01$). In addition, time allocated to ESL-related activities was positively related with mixed bilingual students' reading growth ($\beta = 0.243, p < .10$). Moreover, notably, there was some evidence that receiving in-class ESL services was positively associated with LEP students' reading growth ($\beta = .611, p < .10$) but negatively associated with reading growth for English Monolinguals and Mixed Bilinguals ($\beta = -0.295, p < .10, \beta = -1.274, p < .05$, respectively). Pull-out service was also found to be positively associated with LEP students' reading growth ($\beta = .865, p < .05$). Interestingly, ESL aide service was only significant for English Monolinguals ($\beta = .508, p < .05$). Of note, during the kindergarten year (Growth 1), there was only one main effect for teachers' allocation of classroom time for instruction; that is, for LEPs, a statistically significant effect was found ($\beta = 0.178, p < .05$). There was also no interaction effect present between ELs and non-ELs with respect to teachers' allocation of classroom time for literacy instruction (i.e., ESL*reading instruction).

Table 4-8 Piecewise conditional model standardized estimates and standard errors for ESL programs and classroom reading practices across language profile groups (M12)

	English Monolinguals		**English Bilinguals**		**Mixed Bilinguals**		**LEP**	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Initial Status	-4.571***	0.215	-3.992***	0.509	-4.413***	0.511	-4.398***	0.563
SES	0.527***	0.045	0.474***	0.103	0.019	0.170	0.244	0.153
Female	0.176**	0.087	-0.354	0.350	0.166	0.383	-0.177	0.470
Literacy K	0.115***	0.038	0.107***	0.037	0.144***	0.047	0.147***	0.048
Growth 1	4.101***	0.442	3.749***	0.629	4.311***	0.448	1.039	1.030
Female	0.103	0.141	0.103	0.420	0.027	0.080	0.260	0.296
SES	-0.025	0.072	-0.079	0.186	-0.216*	0.122	0.026	0.263
Literacy K	-0.050	0.063	-0.044	0.056	-0.046	0.057	-0.042	0.052
ESLK	0.240	0.165	0.328	0.305	0.774***	0.283	-0.236	0.374
ESL Time	-0.093	0.071	0.094	0.134	0.243*	0.130	0.079	0.121
In class ESL K	-0.295*	0.173	0.138	0.418	-1.274***	0.339	0.611*	0.322
Pull out ESL K	0.024	0.229	-0.034	0.411	-0.329	0.344	0.865**	0.379
ESL Aide K	0.508***	0.151	-0.099	0.320	-0.320	0.286	-0.071	0.120
Reading Inst. K	0.063	0.045	-0.180	0.172	0.360	0.282	0.178***	0.076
ESL*Inst. K	-0.038	0.039	0.215	0.176	-0.377	0.277	-0.106	0.082
Growth 2	9.475***	0.243	8.339***	1.135	6.199***	0.938	8.300***	0.840
Female	-0.259	0.166	0.729*	0.440	-0.631*	0.331	-0.971**	0.408
SES	-0.454***	0.076	-0.286	0.179	0.229	0.185	-0.022	0.143
Literacy 1st	0.061	0.046	0.065	0.049	0.047	0.035	0.046	0.035
ESL 1st	-0.084	0.283	-0.322	0.371	-0.236	0.237	-0.093	0.316
In class ESL 1st	-0.036	0.325	-0.156	0.148	-0.143	0.382	-0.355	0.258
Pull out ESL 1st	-0.068	0.303	0.606*	0.333	-0.513	0.374	0.421	0.324
ESL Aide 1st	0.308	0.244	-0.037	0.233	0.149	0.188	0.071	0.110
Reading Inst. 1st	0.132**	0.066	-0.002	0.041	-0.083	0.084	1.102*	0.569
ESL*Inst. 1st	-0.130**	0.076	0.008	0.090	0.043	0.109	-1.046**	0.570
Growth 3	3.706***	0.795	4.717**	1.488	3.788***	0.993	2.550**	1.186

Table. 4.8 (continued)

	English Monolinguals		**English Bilinguals**		**Mixed Bilinguals**		**LEP**	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
SES	0.292**	0.125	-0.016	0.374	0.282	0.200	0.235	0.247
ESL 3rd	-0.200	0.188	-0.138	0.563	0.466	0.398	-0.048	0.689
Female	-0.092	0.184	0.439	0.613	-0.489	0.443	0.157	0.668
Literacy 3rd	0.045	0.082	0.049	0.091	0.049	0.090	0.044	0.081

Notes. Chi square = 1721.268 $p<.05$, RMSEA=.046, $p > .05$, CFI= .919, SRMR = 0.050. *ESLK*, *ESL 1st*, and *ESL 3rd* indicate whether the students were ELs or not. *ESL time* indicated the hours allocated to ESL-related activities during kindergarten. *In-class ESL K* and *Pull-out ESL K* are dichotomous variables indicating the type of ESL services provided at kindergarten and first grade. *ESL aide is* a dichotomous variable indicates whether the service was available at kindergarten and first grade for ELs. *Reading instruction* is a composite score indicating teacher coverage of literacy skills emphasized during kindergarten and first grade. ***p<.01 **p<.05 *p<.10

During growth two (i.e., first grade), there were no statistically significant parameters associated with the type of ESL services. Notably, though, the direction of the effects were all negative for in-class ESL services. For the pull-out services, the directions were positive for English Bilinguals and LEPs while negative for English Monolinguals and Mixed Bilinguals. In terms of ESL aides, no evidence was found for its effect in any of the language profile group. However, for English Monolinguals and LEPs, teacher coverage of literacy skills was positively associated with reading growth ($b = 0.132, p < .05;\ b = 1.012, p < .10,$ respectively). In terms of ELs, the effects were also significant for English Monolinguals and LEPs but in the negative direction ($b = -0.130, p < .10;\ b = -1.046, p < .10$ respectively), suggesting that ELs still somewhat lagged behind their non-EL counterparts in these two groups, given the same amount of teachers' literacy instruction emphasis. Although there was relatively weak evidence regarding the positive effects conferred by teachers' emphasis of literacy skills, the effects were in the expected direction (.018 and .109, respectively).

In summary, having an ESL aide did not benefit children speaking other languages—English Bilinguals, Mixed Bilinguals, and LEPs during kindergarten or first grade. It did, however, benefit English Monolinguals who were identified as ELs during kindergarten. In addition, receiving ESL services was found to impact reading growth differently across language background groups over the duration of the study. Notably, both in-class service and pull-out service produced positive effects for LEPs, with the latter being more pronounced (.611 vs. .865). However, for English Monolinguals and Mixed Bilinguals, in-class services seemed to impede their reading growth somehow. Unexpectedly, teachers' focus on reading instruction proved effective and beneficial for English Monolinguals and LEPs only. Further, these positive benefits were not observed for EL students during either kindergarten or first grade. In other words, there still remained a significant gap between ELs and non-ELs with respect to reading growth at these two critical junctures, despite differences in teachers' responses regarding their classroom time allocated to targeted literacy skill developments.

Research Question 4. How Many Unobserved Latent Classes Are Expected and to What Extent Do the Groups Differ with Respect to Their Latent Reading Growth Trajectories? To What Extent Do School/ Classroom, and Student Factors Impact Latent Group Membership?

The last research question examined whether there might be unobserved heterogeneity within latent classes comprising the larger population, each having its own unique growth distribution. If such latent classes were observed, the primary focus of the analysis was to infer the probability of individuals' group membership in particular latent classes from the data utilizing key student variables such as EL status as well as classroom or school variables. As noted by Muthén and Asparouhov (2009), this type of information can be useful in evaluating how school and classroom variables may influence probability of being in one particular latent class versus the others. To examine Research Question 4 in greater detail, I fit the previous growth models to a K-3 subset of the data. This early elementary dataset provided a larger weighted student sample to explore unobserved heterogeneity in the data and to link class membership to background, teacher and school predictors.

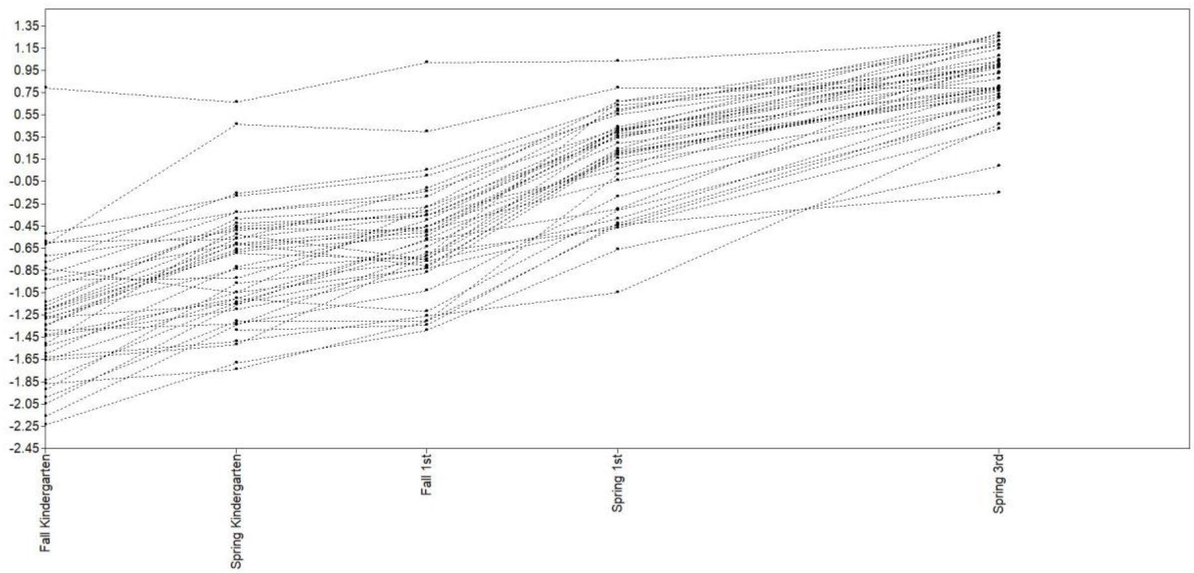

Figure 4-4 Reading growth curves obtained from 40 individuals across five occasions.

Figure 4.4 presents a random subset of growth curves from 40 individuals across the five measurement occasions. Examining the individual trajectories illustrates the considerable variability regarding individuals' initial kindergarten entry scores as well as their growth rates over time. GMM analyses generally proceed from the assumption that population from which the sample was drawn consists of *k* latent classes of unknown size. The first model, which was specified as the latent basis growth model consisting of only one class (i.e., the entire sample), served as the baseline model. The parameters of the time loading vector (Λ) were consistent with the K-8 weighted sample except for the removal of the last time period (i.e., spring third through spring eighth grade), suggesting the congruence of these two samples over the K-3 growth periods studied. Together, the growth parameters described an overall pattern of reading change that covered growth between fall kindergarten and spring kindergarten and between fall first grade and spring first grade.

Building from this baseline model, I fit a series of GMMs (i.e., two-class, three-class, and four-class models allowing for differences in means, means + cov, means + cov + patterns) to the data, using a theoretically meaningful covariate, EL status, to help explain latent class membership because differences between EL and non-EL students in reading achievement have been well documented. In preliminary analyses, the four-class model had no members assigned to the fourth class, so this model was not considered further. Fit statistics for all eight two- and three-class models are reported in Table 4.9.

Table 4-9 Fit statistics for baseline latent growth model, 2-class growth mixture models, and 3-class growth mixture models

	1-class baseline	**2-class Means**	**2-class Means+Cov**	**2-class Means+Cov +Pattern**	**3-class Means**	**3-class Means+Cov**	**3-class Means+Cov +Pattern[a]**	**3-class Means+Cov +Pattern[b]**
Sample size								
N=1	4026	4020.160	3981.172	3952.874	3513.490	390.834	820.862	567.077
N=2		5.840	44.828	73.126	315.987	2641.745	629.624	2553.628
N=3					196.523	993.421	2575.514	905.294
Fit statistics								
# of parameters	14	17	23	30	25	37	39	39
Entropy	1.000	0.998	0.986	0.965	0.844	0.682	0.543	0.545
AIC	19278.66	5639.219	5583.641	5495.452	5123.850	4753.982	4807.602	4762.022
BIC	19366.87	5746.328	5728.553	5684.468	5281.363	4987.101	5053.323	5007.743
ABIC	19322.38	5692.310	5655.469	5589.142	5201.924	4869.532	4929.398	4883.818
Vuong-Lo-Mendell-Rubin LRT p value	NA	.000	.000	.000	.003	.000	.045	.000
Lo-Mendell-Rubin adjusted LRT p-value	NA	.000	.000	.000	.004	.000	.046	.000
Parametric bootstrap LRT p-value	NA	.000	.000	.000	.000	.000	.000	.000

[a]SW2 trajectory varies between latent classes.
[b]SW1 and SW2 trajectories vary between latent classes.

The model selection process began by examining and interpreting the parameters estimates and output details of the models. Several statistical and practical criteria can be used to determine the suitability of a particular number of extracted latent classes to the data. One is whether the particular solution generated can be replicated over a number of random starts. Because mixture models require iterative estimation procedures, it is important to use multiple sets of estimation random start values to ensure the solution reached is a global rather than local solution, given a range of possible model start values. If results cannot be replicated, it can be an indication of problems with the proposed model (Berlin, Williams, & Parra, 2014). Except for the and 2-$Class_{means+cov+\text{pattern}}$ model, the remaining seven models all had messages in Mplus stating that the best loglikelihood value has been replicated, which indicated the model converged on a "global" solution and appropriately represented the data. I then had to increase the random start value for the 2-$Class_{means+cov+\text{pattern}}$ model to achieve model convergence. Additionally, I did not observe any negative variances or correlations greater than 1.0 in these models—evidence of poor model fit--as negative variance estimates are one indication that the model was not appropriate for the data (Ram & Grimm, 2009).

Next, the fit statistics were employed (see Table 4.9). Looking for the models with the lowest information criteria (i.e., AIC, BIC, ABIC), the 3-$Class_{means+cov}$ model and 3-$Class_{means+cov+\text{pattern}}$ with both slopes varying across the groups (i.e., last column) emerged as obvious improvements over the baseline model and other models. However, the 3-$Class_{means+cov}$ model demonstrated a higher entropy (.682 vs. .545), hence indicating a higher degree of confidence in classifying the groups. According to Clark and Muthén (2009), entropy values of .40, .60, and .80 represent low-, medium-, and high-class separation. Furthermore, the probabilities associated with several associated likelihood ratio tests provided as output were all statistically significant ($p < .05$)—indicating that the 3-class (i.e., the alternative, less restrictive) model fit the data significantly better than a model with one less class. Taken together, the 3-$Class_{means+cov}$ model was chosen as the most appropriate for the data.

Figure 4.5 graphically illustrates differences between the three homogeneous groups that emerged from the data, and I subsequently labeled them as high- (Class 1), medium- (Class 2), and low-achieving (Class 3) (Class 3) in reading. As shown, the medium-achieving class represented the typical growth pattern, as this class had an estimated class proportion of greater than 0.5—that is, the class represented more than 50% of the overall population (Maysn, 2013).

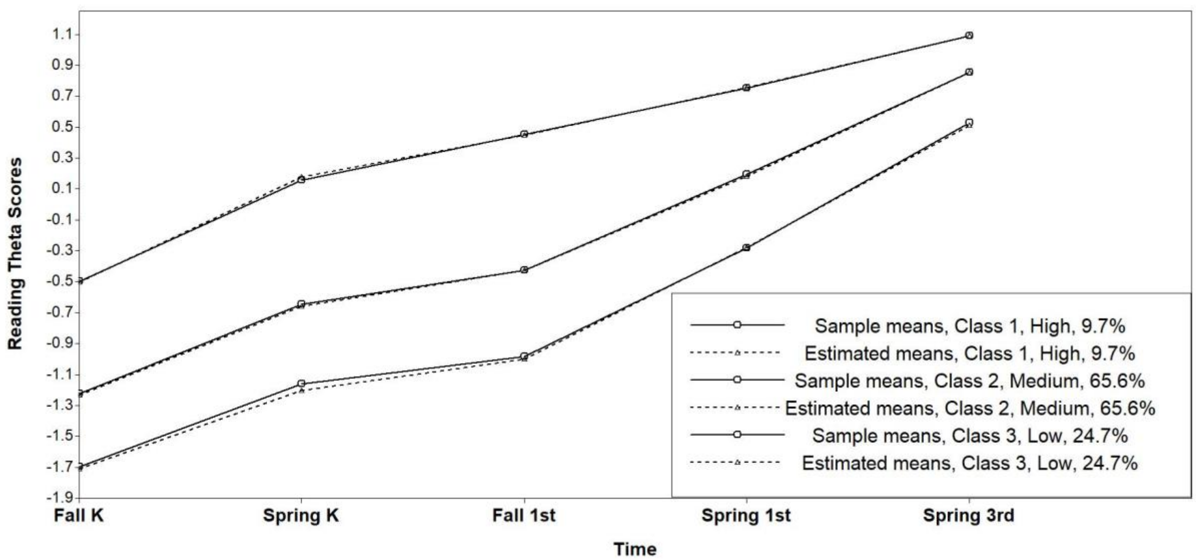

Figure 4-5 Sample and estimated means for three latent classes across 5 occasions.

Table 4.10 presents information on the classification of individuals into the latent classes as well as the model parameter estimates for the chosen model, that is, three latent classes with equal means and covariance structure. Class 1 was estimated, based on the sum of individual probabilities of group membership, to contain roughly 10% ($N_1 = 390.834$) of the sample. The table also displays information related to the quality of the classification given posterior probabiliities. On average, individuals in Class 1 had a .889 probability of assignment to this latent class and complementary small probability of being in either of the other two classes. Class 2 was estimated to contain roughly 65.6% (N_2 =2641.745) of the sample, and, on average, they had a .859 probability of being assigned to the second latent class. Class 3 was estimated to contain roughly 24.7% ($N_3 = 993.421$) of the sample and, on average, had a .812 probability of being assigned to this latent class. Like the entropy statistic, high probabilities indicate that the classes are distinct from each other. Specifically, approximately 89%, 86%, and 81% of the students assigned to these three latent classes fit their respective category, while only 11%, 14%, and 19% of the students in that given class were not accurately described by that category.

Looking at the unstandardized parameters more specifically, on average, the medium-achieving class had an initial status mean of -2.978 (kindergarten entry), growth one mean of 2.668 (growth during kindergarten) and growth 2 mean of 5.563 (growth during first grade). On the other hand, the high-achieving group represented a smaller proportion of the students in the overall sample (i.e., 10%) and, on average, this group had a higher initial status mean (-0.916) but smaller growth one (2.128) and growth two (4.361) means compared with the medium-achieving group. Finally, the low-achieving group, consisting of roughly 25% of the overall sample, started considerably lower at kindergarten entry (mean = -5.228) and grew at a lesser rate during both kindergarten (2.281) and first grade (3.933) compared to the reference mid-achieving group. Notably, however, the low-achieving group demonstrated faster growth rate than the high-achieving group though, a finding congruent with that of multi-group analyses.

In terms of variability, class one had the largest variability at initial status and during kindergarten (slope one); whereas class three had the largest variability during first grade (slope two). All the covariances were significant across three classes ($p <$.05) and differed only in magnitude except for class one, where the covariance between slope one and slope two was positive (0.007) rather than negative.

Table 4-10 Model parameter estimates for the chosen model: 3-Class (means+cov)

	High-Achieving (Class 1, 10%)	**Average-Achieving** (Class 2, 65.6%)	**Low-Achieving** (Class 3, 24.7%)
Estimated sample size	390.834	2641.745	993.421
Average probability of class membership	0.889	0.859	0.812
Factor Loadings			
Slope 1 loadings = 0, 1, 1.4, 1.4, 1.4			
Slope 2 loadings = 0, 0, 0, 1, 2.1			
Latent variable means[a]			
Intercept mean	-0.916 (0.085)	-2.978 (0.059)	-5.228(0.272)
Slope one mean	2.281 (0.014)	2.668 (0.048)	2.128(0.083)
Slope two mean	3.933 (0.010)	5.563 (0.227)	4.361(0.179)
Latent variable variances and covariances[b]			
Intercept variance	0.302 (0.025)	0.171 (0.007)	0.107 (0.009)
Slope one variance	0.089 (0.008)	0.047 (0.002)	0.057 (0.008)
Slope two variance	0.006 (0.001)	0.012 (0.001)	0.027 (0.002)
Intercept-slope one covariance	-0.151 (0.014)	-0.065 (0.004)	-0.017 (0.004)
Intercept-slope two covariance	-0.020 (0.003)	-0.015 (0.002)	-0.017 (0.004)
Slope one-slope two covariance	0.007 (0.002)	-0.003 (0.001)	-0.017 (0.003)

Notes. Standard errors in parentheses.
[a] standardized estimates were reported.
[b] unstandardized estimates were reported as factor variances were not standardized to one.

After developing the latent trajectory classes, it is of interest to examine the manner in which the latent classes differed with respect to two of the key variables in this study; that is, EL status and language background. Table 4.11 presents these disaggregated results. In particular, the table suggests EL students were considerably more likely to be represented in the low-achieving reading trajectory class. Similarly, students who predominately spoke a language other than English at home (i.e., LEP students) were more likely to be members of the low-achieving reading trajectory class than members of either of the other classes. In contrast, English Monolinguals were relatively equally distributed in the average- and high-achieving groups and less likely to be in the low-achieving group. English Bilinguals were more likely to be members of the high-achieving trajectory class than members of the other two classes.

Table 4-11 Variable means and standard deviations, disaggregated by latent trajectory class

	Low-Achieving		**Mid-Achieving**		**High-Achieving**	
	M	SD	M	SD	M	SD
EL	0.434	0.450	0.250	0.432	0.294	0.456
Language background						
English Monolinguals	0.605	0.489	0.811	0.391	0.748	0.435
English Bilinguals	0.094	0.292	0.078	0.268	0.128	0.335
Mixed Bilinguals	0.089	0.285	0.058	0.235	0.075	0.265
LEPs	0.211	0.407	0.054	0.226	0.049	0.217

Results for multinomial regression portion of the model are summarized in Table 4.12 Model 1 was the baseline model where EL status was added as covariate to predict the number of latent classes. Here, the likelihood of inclusion is compared to the likelihood of inclusion in average-achieving group as the normative achieving reference group, as it represents the majority of the students. Each coefficient represents the logit estimate of the impact of the covariate on the likelihood of inclusion in each of the two latent trajectories in comparison to the inclusion in the reference group. Further, significant coefficients were converted to odds (e^{logit}) to aid in interpretation. As shown in Model 1, EL status had a significant positive, statistically significant impact on the probability of students' inclusion in the low-achieving reading group as opposed to the mid-achieving group. More specifically, EL students were approximately 2.12 times more likely to be in the low-achieving category than the mid-achieving trajectory, consistent with Table 4.11 (which shows the low-achieving class made up of 21% LEPs and the average class of only 5.4% LEPs), and confirming the extensive past research on the negative impact of EL status on reading achievement. In contrast, EL status was not significant in predicting students' inclusion in the high-achieving class versus reference class ($p > .05$). This lack of relationship is also explained in Table 4.11, where 4.5% of the average-achieving class was made up of LEP students and 4.9% in the high-achieving class.

Table 4-12 Multinomial logistic regression model estimation of the likelihood of latent class trajectory categorization in comparison with mid-achieving as the reference group

	Low-Achieving		**High-Achieving**	
Variable	Coefficient	Odds Ratio	Coefficient	Odds Ratio
Model 1				
Student Background				
EL status	0.753***	2.123	0.083	
Model 2				
Student Background				
EL status	0.078		0.022	
SES composition	-1.018***	0.361	0.522***	1.685
Home literacy	-0.110		0.568***	1.765
Female	-1.114***	0.328	-0.191	
Classroom variables				
Reading instruction	0.149		0.436**	1.547
Time for ESL activities	0.055		0.180	
Teacher preparation	0.144		-0.175	
Teacher experience	-0.108		-0.002	
School variables				
Title 1	0.447		-0.460**	0.631
School Improvement process	-0.429*	0.651	-0.019	
Percent of LEP	0.021**	1.021	-0.008	
Years of ESL programs	-0.238**	0.788	0.013	
Range of ESL services	0.235		0.007	

Notes. Parameter estimates and odds ratios for each respective latent class are in comparison to the reference class mid-achieving as a function of the covariates.
****p*<.01 ***p*<.05 **p*<.10

Model 2 added a set of student background, classroom, and school characteristics to assess their impacts on the formation of group membership (summarized in Table 4.13). Overall, student inclusion in the low-achieving trajectory was influenced the most if the school had a lower school improvement process score $(-)$, a higher proportion of LEP students $(+)$, fewer years of ESL programs available $(-)$, lower family SES $(-)$, and lower scores on reported home literacy practices $(-)$. In contrast, significant coefficients for the high-achieving trajectory class were higher family SES $(+)$, stronger home literacy practices $(+)$, greater teacher emphasis on allocating time for reading instruction $(+)$, and not being in a Title I school $(-)$. Notably, the statistically significant negative coefficient associated with female indicated the likelihood of inclusion in the low-achieving group was associated with being male.

Table 4.13 presents the multiple regression estimate effect sizes for the adjusted intercepts and slopes with covariates for each of the three latent classes, highlighting the most significant variables influencing reading achievement scores at fall kindergarten entry (initial status), as well as reading growth patterns during kindergarten and first grade (i.e., slope 1 and slope 2, respectively). Note that covariates were grouped at the individual level, classroom level, and school level; with the classroom- and school-level covariates regressed only on the slopes, as illustrated in Figure 3.3 of Chapter 3. One of the main advantages of GMM is that the model simultaneously estimates the intercepts and slopes for each separate latent trajectory class; hence, there are three different regression models. As opposed to standard OLS or HLM regressions, the intercepts for a GMM are of substantive interest because each of the latent classes has its own intercept and slope (Bowers & Sprott, 2012). Thus, different model-estimated mean values for the intercepts can be interpreted as the average reading scores at fall kindergarten for children in each of the three latent classes. In addition, the GMM estimates the influence of covariates on the intercepts and estimates the amount of variance explained by the included covariates.

Table 4-13 Multivariate standardized regression estimates on latent growth factors for each identified latent growth class

Model 2	**Low-Achieving**	**Average-Achieving**	**High-Achieving**
Initial Status	-5.388***	-3.056***	-0.805***
Student Background			
EL status	-0.075	-0.017	-0.028
Home literacy	0.063	0.018	-0.017
SES composition	0.218**	0.364***	0.275**
Female	-0.165**	0.057*	-0.053
R square	0.099	0.137	0.083
Slope One mean	1.998***	2.534***	2.078***
Student Background			
EL status	0.001	0.036	0.009
Home literacy	0.085	-0.022	-0.040
Family SES	0.123	-0.167***	-0.188*
Female	0.098	-0.024	0.087
Classroom variables			
Read instruction	-0.058	0.068*	0.002
ESL time	-0.043	-0.004	0.003
Teacher experience	0.005	0.007	0.003
Teacher preparation	-0.017	0.008	0.035
School variables			
Title I	0.133	0.010	0.000
School improvement	-0.065	0.060*	0.025
Percentage LEP	0.028	0.045	0.009
Years of ESL programs	-0.298*	0.008	-0.059
Range of ESL Services	0.351*	-0.044	0.020

Table 4.13 *(continued)*

Model 2	Low-Achieving	Average-Achieving	High-Achieving
R square	0.115	0.042	0.053
Slope Two mean	4.291***	5.349***	5.288***
Student background			
EL status	0.125*	-0.089**	0.018
Home literacy	-0.056	0.065	0.156
Family SES	-0.083	-0.025	-0.189
Female	-0.035	-0.013	-0.107
Classroom variables			
Reading instruction	-0.008	-0.001	-0.055
School variables			
Title 1	-0.134*	-0.027	0.007
School improvement	0.055	-0.074*	-0.100
Percent of LEP	0.040	-0.078	-0.388**
Years of ESL programs	0.020	0.025	0.458**
Range of ESL services	-0.135	0.058	-0.114
R square	0.055	0.022	0.224

Notes. Coefficients are expressed as effect sizes as a change in Y standard deviation units for a one standard-deviation change in X. ***p<.01 **p<.05 *p<.10

As shown in Table 4.13 (top section), both family SES and female were significant and accounted for about approximately 14% and 10% of the variance in the average-achieving class and low-achieving class, respectively; only family SES was significant for the high-achieving class, accounting for 8% of the variance for initial status at fall kindergarten entry. This may indicate the relative advantage of being female in average-achieving or disadvantage in low-achieving reading latent classes, whereas no such gender effect was observed in the high-achieving group. Family SES was significant for all latent classes, consistent with existing research in its robust effect on children's literacy and language development as early as kindergarten.

The mid- and bottom-sections of Table 4.13 present the slope coefficients for the three latent class trajectory models. For slope one (i.e., fall K-spring K), about 12% of the variance in the low-achieving class was explained by school covariates, years of ESL program and range of ESL services, while none of the school covariates was significant in explaining variance in the high-achieving group, indicating the differential impacts of school processes in students' inclusion in the low- versus high-achieving groups. For the average-achieving group, the slope coefficient associated with reading instruction was significant $(+)$, suggesting the positive impact of teacher emphasis of targeted literacy skills for the majority of the children classified in this group. Note that family SES was found significant $(-)$ for both average- and high-achieving groups, suggesting it compounded the negative effect of EL status. For slope two (i.e., fall 1st - spring 1st), school covariates, percentage of LEPs $(-)$, and years of ESL programs $(+)$ were significant and accounted for about 22% of the variance in reading growth during first grade for high-achieving group. Consistent with prior research, higher concentration of LEPs was negatively associated with EL students' reading growth, while longer periods of ESL programs boosted EL students' reading growth. For the low- and average-achieving groups, EL status was significant but in opposite directions, suggesting EL students grew at a slightly faster rate than their non-EL peers in the low-achieving group and, in contrast, EL students grew at a significantly slower rate in the average-achieving group. Further, over time, school covariates explained relatively more variance in slope one than slope two for this low- and mid-achieving groups, showing a reverse pattern different from the pattern within high-achieving group.

The value of the GMM analyses is in revealing differences among the latent classes defining substantial subgroups of students with similar patterns of reading growth during their K-3 years. The analyses present a richer story. Thus, for the two categories associated with low-achieving and high-achieving reading performance, these findings replicate and extend much of the literature on the variables most associated with reading trajectories, but with two important advances. First, rather than estimating the direct effect of each covariate on reading growth, the model estimated the effect of each covariate on the mediating latent class trajectory variable. This implies that the indirect effect of school variables on reading growth can be seen, for example, by the negative effect of school improvement process (as shown in Table 4.12) increasing the probability of being in the poorly developing reading trajectory class and the positive effect of greater percentages of EL students being associated with membership in this same class. In other words, these school variables had an indirect effect mediated by the student background latent class variable (Muthén & Asparouhov, 2011). Second, as summarized in Table 4.13, the different patterns of covariates affected the growth rates within each latent trajectory class. As hypothesized, school covariates had differential impacts on the three latent groups with regard to reading growth during kindergarten and first grade. Although the set of statistically significant predictors was modest, the usefulness of this approach extending theory by examining emergent relations in the data was well illustrated

Chapter 5 Discussion and Implications

In this chapter, I briefly review the background and purposes in conducting the study. I then discuss the results pertaining to each research question and its implications as well as highlight several limitations to consider in evaluating the results. Finally, I conclude with thoughts on future research.

Background and Purposes in Conducting the Study

An extensive line of previous research investigated the influences of sociocultural factors on children's literacy and language development that go beyond individual characteristics, such as parent education, family income, and home literacy practices. Recently, this line of inquiry was extended to include a subpopulation of children who speak a home language other than English, considered as language minority children. Results of large-scale standardized test scores revealed a sizable gap between these language minority children and their English monolingual counterparts, thereby propelling researchers to understand the mechanisms underlying these language minority children's reading development. Unfortunately, most prior research studying language minority children's academic performance was fraught with technical issues, one example being the cross-sectional nature of the analyses. Cross-sectional data preclude researchers from examining whether a difference in achievement observed at a single point in time between language minority and English monolingual students represents a stable gap that persists over several years or is more idiosyncratic, given the limitations of measuring achievement differences accurately at a single point in time. Cross-sectional data are also limited in discovering relationships between covariates and outcomes that may change in size or direction over time.

Previous studies also suffered from conceptual limitations, one being that because they often treated language minority children as a homogeneous group—uniformly low in English proficiency—researchers failed to uncover the nuances in their developmental patterns that distinguished them from their English monolingual peers. Critical to unpacking their language minority status concerns the ways in which home language environment can be captured. In the past, students' home environment was treated typically as a demographic control in conventional modeling approaches, which emphasized the size of achievement gaps existing between language minority students (or amongst themselves) and their English monolingual counterparts at one or more assessment points. A shortcoming, however, was that this approach precluded researchers from developing models within each language subgroup that fully investigate existing variability in achievement status and growth exhibited within each subgroup that may be of substantive interest when studying developmental patterns across groups of students having diverse backgrounds and corresponding English language needs.

Given some noted conceptual and technical limitations in previous research on the literacy development of language minority students, latent curve analysis (i.e., piecewise growth modeling) was a more promising and appropriate analytic approach, such that it provided a more nuanced examination of EL students' literacy growth during a key period in their literacy development (Saracho, 2017) while simultaneously considering their different home environments (e.g,, family SES, home literacy practices), language backgrounds, and English proficiency levels at kindergarten entry. Latent curve analysis aids the investigation of developmental processes that evolve over time in the context of multi-stage growth and multiple processes. As pointed out by Muthén and Curran (1997), once the single-level or multilevel linear model is put into a latent variable modeling framework, many general forms of longitudinal analysis are possible, such as specifying mediating variables which may influence the developmental process and moderation analyses which may isolate multiple causal processes operating across groups (i.e., in this study, language background groups).

With a developmental perspective at the center of the research, the interest was not so much in the level of a certain outcome at a particular time point as it was in examining the growth trajectory as it evolves across multiple time points. In other words, it was of interest to see how relationships between trajectories of early reading growth process relate to reading growth patterns in subsequent time periods. This type of dynamic analysis where outcomes and covariate impacts on the outcomes may be evolving over time is more consistent with the nature of developmental processes. Notably, the multi-group latent curve analyses facilitated examining whether children of diverse language backgrounds exhibited similar or dissimilar reading growth trajectories, as well as testing propositions regarding the mechanisms relating the key variables in the study—family SES, home literacy practices, EL status, and children's reading growth—and their relative invariance or variance across four language profile groups. Additionally, school and classroom contexts and processes were examined, as they constituted extra-familial language environments that likely affected children's English reading growth.

In addition to investigating nuances in student growth across language background groups based on home language use and the OLDS assessment, I used a relatively under-utilized analytic approach, growth mixture modeling, to uncover unobserved heterogeneity in latent reading trajectory classes, with school-labeled EL status as one covariate to explain latent class membership. This exploratory approach identified several latent classes that had their own initial status and growth means, as well as their own unique estimates of variance in the mean growth parameters and covariate influences on the growth parameters. Specifically, each latent class represents a qualitative different reading growth trajectory within the data, and each pattern of relations in terms of family SES, home literacy practices, and school contexts and processes was allowed to vary across the classes. Different from conventional school effects research, school context variables were conceptualized to affect students' reading achievement both directly (i.e., exerting effects on the initial status and growth parameters) and indirectly through their influence on the probability of student membership in the latent classes formulated at the student level. Importantly, this approach provided considerable flexibility in examining the mediating role of school contexts and processes in students' inclusion in each of the three latent reading trajectories. It shed a sharper light on the distinct pathways by which school variables affect students' reading growth over time in comparing both direct and indirect effects (i.e., on growth factors and latent classes, respectively).

This study built upon and extended the previous literature in examining the reading growth trajectories between language minority children vis-à-vis their English monolingual peers on several fronts. First, utilizing a national longitudinal data that oversampled underrepresented language minority groups over an extended period of time facilitated the examination of students' reading growth trajectories within their particular group (i.e., each with differing English proficiency skills) and, in comparison to the other language background groups from early childhood years through their upper elementary and middle school years. Compared to school district data used in prior longitudinal studies, ECLS-K administered large-scale home surveys, which facilitated capturing students' differing English language skills through their home language background more thoroughly than simply using school-designated EL status alone. As argued previously, EL definition tends to take on different meanings for different school districts. Second, multiple-group latent curve analysis and growth mixture modeling enabled examining key theoretical propositions and relationships concerning the relative contribution of multiple contexts to children's development of reading and to the relationship of family SES to early literacy measures. Ecological and developmental frameworks suggest ways environments may interact with one another and may thus attenuate or amplify their effects on social and cognitive development. Third, theorizing unobserved heterogeneity in children's reading achievement as latent classes through which school characteristics could influence their reading growth patterns illustrated new potential in in this field for exploring the mechanisms relating school-labeled EL status, school contexts and processes, and development of reading. A closer examination of the results follows.

Discussion of the Results

Reading growth trajectories in the full sample. Consistent with prior research (e.g., Lee, 2010; Liu, Liu, & Hau., 2016), initial visual and statistical analyses suggested that reading achievement growth between kindergarten and eighth grade was not linear. The piecewise latent curve growth model strongly confirmed the curvilinear nature of students' reading growth over an extended period of literacy development, accounting for the reduced rates of growth in late elementary and upper middle school. Specifically, the model with three separate growth factors (i.e., Model 3) which facilitated estimating separate growth rates corresponding to specific learning stages (i.e., fall kindergarten through fall grade 1, fall grade 1 through spring grade 3, and spring grade 3 through spring grade 8) demonstrated considerable improvement in model fit compared to the other two alternative models with one or two growth factors. Importantly, quantifying the change in reading achievement over grades K-8 with distinct rates of growth modeled at critical junctures enabled investigation of the differences in reading during early and later grades. Further, the inclusion of time-varying predictors pertaining to home literacy practices and classroom instructional practices in research questions two and three allowed me to assess the extent to which variation in reading growth was accounted for by these theoretically significant factors.

Many features of the reading achievement growth modeled in this study were consistent with prior research. For example, children's reading scores were significantly lower at fall kindergarten entry than during elementary and early middle grades. Examinations of relationships between achievement status indicators revealed that reading scores at kindergarten entry were positively correlated with later reading scores—a robust linkage well established in the literature where early reading achievement predicted achievement in subsequent grades (e.g., Alexander, Entwisle, & Horsey, 1997; Chatterji, 2006). Interestingly, there was mixed evidence regarding correlations between reading scores at kindergarten entry and later reading growth factors based on the latent curve analysis and growth mixture analysis, such that interrelationships between initial achievement status and subsequent growth slopes were all significant in the mixture analysis, whereas the relationship between initial status and growth slope three was found significant in the latent curve analysis. In part, it might be the differences in the growth periods examined in two parts of the analyses, with a third slope factor (covering grades 3-8) included in the latent curve analysis. Nonetheless, the negative significant relationship between initial status and later growth detected in the study ran contrary to previous studies examining math achievement, where students who entered kindergarten with poorer mathematics skills demonstrated less absolute growth over time as compared to their higher-achieving peers (Bodovski & Farkas, 2001; Geary et al., 2009). Further, from kindergarten through first grade, variance in reading achievement scores tended to shrink over time, indicating that students' learning experience tended to become more similar during school (see also Quinn, Cooc, McIntypre, & Gomez, 2016 and Shanley, 2016).

The result indicating that students demonstrated faster average learning rates during kindergarten and first grade compared with late elementary and middle school (see also Bloom, Hill, Black, & Lipsey, 2008) could be attributed to a number of factors. For one, it could simply be that students learn at a faster rate in early grades because they have more flexible and malleable minds and generally positive attitudes toward school (Stipek & Tannatt, 1984) or because there is more to learn as they enter kindergarten. Notably, the average learning rates were higher during first grade than kindergarten, providing initial evidence regarding the effectiveness of classroom practices with slightly more emphasis on phonics during this transition from preschool into kindergarten and the primary grades, such as phonemic awareness, letter recognition, phoneme segmentation, and word reading fluency that are found to support later reading competence (Saracho, 2017). On the other hand, the reduced reading growth during later grades revealed the challenges in enhancing children's ability in passage reading comprehension, as it entails skills that cannot be easily mastered, for example, including indefinite sets that permit continuous growth in vocabulary breadth and comprehension (Liu et al., 2016; Paris, 2005). It is apparent that language-minority children can keep pace with their native English monolingual peers when the instruction focus in on basic word-level skills, but lag behind when the instructional focus turns to reading comprehension and writing (Ballantyne et al., 2008). In this regard, students' faster rates of acquisition in pre-reading skills, such as letter recognition, alphabet knowledge, and word decoding, cannot be readily translated into higher command of skills in order to engage in the practice of reading for meaning.

In one study that may be relevant to the differential patterns of reading growth observed in the current study, Xue and Meisels (2004) found that phonics instruction was equally effective for children regardless of their initial ability, as opposed to the conclusion of the National Panel Reading report that such instruction was more effective for at-risk children (Ehri, Nunes, Stahl, &Willows, 2001). However, Xue and Meisels noted the effect of integrated language arts instruction on children's direct test scores was differentiated according to children's initial performance. Specifically, when family SES, child characteristics, and phonics instruction were held constant, children with lower entering literacy skills and knowledge did not benefit greatly from integrated language arts instruction, while children in higher initial performance categories learned more when they were exposed to an increased level of such instruction. This result suggests the need to delve deeper into the types of reading instruction teachers use with children of various language backgrounds and skill needs.

Reading growth trajectories of different language profile groups. Multi-group analyses revealed more fine-grained findings that would have been masked had children been lumped into one group—language minority children as represented solely by EL status. Following Han's (2012) study using the ECLS-K data, in the current study, I classified language minority children into four language profile groups by their home language use patterns and the timing of passing OLDS English proficiency test provided in the ECLS-K study during early assessment waves. I combined the non-English Dominant Bilinguals and non-English Monolinguals from Han's language groups to create the LEP group because I applied the appropriate K-8 longitudinal sampling weight and therefore had a considerably smaller sample. Although Han's results suggested that students' home language background only accounted for minimal variation in between-person initial reading status and between-person growth rates (generally less than 5%), because of the multiple-group specification, I noted a more complex pattern of reading growth among children of different language backgrounds. More specifically, in my study, English Monolinguals and English Bilinguals were indistinguishable in reading development; that is, no gaps were observed between these two groups spanning from kindergarten through grade eight. Mixed Bilinguals started with considerably lower reading scores at kindergarten entry than these other two groups but demonstrated significantly greater growth during their kindergarten year. During later growth periods, they grew in reading at a comparable rate with their English Monolingual and English Bilingual counterparts.

In contrast, LEPs lagged considerably behind the other three groups over the duration of the study. Notably, though, this group exhibited significantly greater reading growth than the other groups during first grade, but this increased rate was not sustained over time to allow them to achieve qualitatively different growth profiles. These results are consistent with existing studies unpacking language minority background by delving into students' varying degree of English proficiency status; that is, language minority students with full English proficiency demonstrated similar growth patterns and rates with their native English-speaking peers, whereas language minority students with limited English proficiency status were continuously behind in reading development from kindergarten through grade five (Keiffer, 2008). Further, the result suggesting LEP students experienced greater growth during first grade converged with the conclusion of the National Panel Reading report that conventional curriculum targeting phonics instruction was more beneficial for children at risk—described as children from low-income families with limited English proficiency (Ehri et al., 2001).

Furthermore, in order to disentangle the confounding effects of ethnicity from English proficiency status in children's reading achievement, Han (2012) conducted separate analyses in the Latino and Asian subpopulations and found such results were still robust. In a related vein, preliminary results of my study showed no significant effects of ethnicity background except for Hispanic children, who had significantly lower test scores than their Caucasian peers at fall kindergarten entry. A couple of explanations may be plausible regarding this result. First, by applying a longitudinal sample weight, the present study had a substantially smaller sample size compared with studies that did not do so (see Han, 2012; LoGerfo et al., 2006), thereby reducing the power in detecting significant differences by ethnicity, given there were seven of them identified in the ECLS-K study. In contrast, the results from such studies not applying appropriate weights may result in more findings of significance than when proper sample stratification is considered. Second, compared to ethnicity background, in the current study, language background seemed to be more pronounced in revealing the differential growth rates, supporting the view that English proficiency status mattered more in children's development of reading skills (Lesaux et al., 2010). This finding helps debunk the myths around ethnicity-achievement gaps and lessens the reification of stereotypes.

Results from growth mixture analyses were largely consistent with the multi-group latent curve analyses in terms of reading growth trajectories, albeit with a few notable exceptions. First, three homogeneous reading trajectories across seven waves of reading assessments were found, as opposed to four reading trajectories as designated *a priori*, since English Monolinguals and English Bilinguals virtually experienced the same growth rate patterns. This may suggest that language minority status and EL status, two terms used interchangeably in the dual language literature, are each useful in distinguishing children's English reading abilities, both of which aided in capturing the heterogeneity in language minority children's varied reading outcomes. Importantly, the current study found that EL status differed dramatically across the four language background profiles, with under 20% identified as needing language services among English Monolinguals during first grade and almost 90% identified as needing services among LEPs. This finding is congruent with an earlier study exploring sources of reading comprehension difficulties among language minority learners and native English speakers during early adolescence, which also found three reading skill profiles of students across these two populations (Lesaux et al., 2010). Importantly, the findings of the current study suggest treating language minority students as a separate group based on their school-designated EL status may not be appropriate.

Second, the GMM results suggested the three reading latent classes identified (i.e., each representing student subgroups of considerable size) shared similar growth patterns, albeit with differential patterns of covariate influences, corresponding to the growth patterns of the *a priori* language profile groups. Specifically, on average, all three profile groups demonstrated greater reading growth during first grade than kindergarten, and they were all statistically significant. In addition, the low-achieving profile group, with more struggling readers, grew much faster than the high-achieving group with relatively fewer struggling readers during first grade. Note that these two contrasting profile groups differed most with respect to the proportion of LEP and EL students; that is, with four times as many LEPs and 1.3 times as many ELs in the low-achieving group.

Third, a distinct feature of the GMM analyses is each reading profile group had its own unique variance and covariance structure. The results suggested that the high-achieving profile group, consisting of 10% of the overall sample, exhibited the largest variability in initial reading achievement status, with follow-up analyses confirming this “emergent” mixture of children with rapid growth over their K-3 years was varied in terms of language background and English proficiency status. This is an important finding in the context of the study's overall goals in that it provides empirical support for the view that language minority children are not uniformly low in English proficiency skills during their early reading development.

Family SES, home literacy practices, and children's reading development. A second goal of the study was to examine the extent to which family characteristics exert their influence on children's reading development, which were hypothesized to vary across different language background groups, as suggested by prior research. Results were broadly consistent with prior research in several aspects. First and foremost, multiple-group SEM analyses clearly indicated that family SES explained away a moderate portion of variability in children's reading achievement spanning from early childhood to late elementary school years, especially during kindergarten and first grade, across all groups of children irrespective of English language proficiency skills. Moreover, in terms of the three indicators defining family SES, results converged with prior research indicating all of them were robust predictors, but maternal education was more pronounced for children speaking little English at home compared to children of other language backgrounds (see Bornstein & Bradley, 2003; Mistry et al., 2008). This finding replicates several existing research studies and highlights the important role maternal characteristics played in language acquisition skills among children of low-income and minority families. Second, in the current study, literacy practices, resources, and relationships associated with the family context were most closely associated with reading gaps at the initial kindergarten assessment. The importance of the experiences within the family context for early reading is apparent, as most children experienced little formal schooling by the first assessment. Specifically, the results suggested that the relationship between family SES and children's initial reading performance was mediated by home literacy environment, number of books available in the home to the child, and the provision of other literacy activities and resources outside of home. This is a useful finding implying that, although it may be difficult to alter family SES, interventions in school can reduce the adverse effects of family mediators on developmental processes.

Somewhat surprisingly, there was little evidence supporting the view positing that family SES principally influences children's reading development indirectly through more proximal and mediating processes, such as the quality of home literacy practices (see Conger & Donnellan, 2007). In the current study, family SES chiefly affected children's reading achievement growth in a direct manner across all language background groups. In other words, although family factors were most strongly associated with SES differences in children's reading competence at the initial kindergarten entry, they were less associated with differences in gains or lack of progress in children's reading performance up to early middle school—a finding consistent with existing research using ECLS-K data (Aikens & Barbarin, 2008). In contrast, in Mistry et al.'s (2008) study, the indirect effects of home literacy practices were identified as the principal mechanism through which family SES influenced children's early reading skills in both immigrant and native families, using a longitudinal dataset from National Early Head Start Research and Evaluation Project.

A few explanations may be plausible for the discrepancies in these two sets of findings. First, although family SES in both studies consisted of maternal characteristics, measures for family income differed in ways that may have affected the extent to which family circumstances were captured accurately. For example, family income was measured as income-to-needs ratios for each participating family at two time points in Mistry et al's (2008) study, while in ECLS-K, family income was self-reported as consisting of 13 categories at the onset of the study. Second, the self-report measures of home literacy environment may have differed considerably across the studies, as a diverse array of items was used in both studies to assess the quality of literacy and language stimulation. In sum, the different ways in which family SES and home literacy practices were defined presents some challenges in comparing the results across studies adequately using different datasets. Future research can further examine this issue concerning construct and concurrent validity of these two measures.

Different patterns of covariate influences in terms of family SES and home literacy practices and the degree to which they were able to account for the variability in growth rates clearly indicated the moderating effect of language background on reading achievement status and growth. Stated differently, the paths from family SES to literacy practices and reading growth outcomes varied across children with different language backgrounds. For example, the associations between SES and home literacy practices were found to be robust during the last growth period, regardless of children's language backgrounds, although the mediating mechanism of home literacy practice was salient only among Mixed Bilinguals. Further, family SES and home literacy practices were able to explain more variability in reading growth rates during first grade for English Monolinguals and English Bilinguals than for Mixed Bilinguals and LEPs (i.e., less than 10% in the last group). Clearly, the robustness of the relationship was most pronounced among students with an English-dominant background, suggesting the pervasiveness and dominance of the SES-literacy mechanism among mainstream English-speaking families. On the other hand, the inability to explain a large proportion of the variance in reading growth rates, especially for LEPs, lends support to the contention that proposed measures of family SES may not be as sensitive to the circumstances of language minority families, comprising a large percentage of immigrant population, as they could have been

(Fuligni & Yoshikawa, 2003). Other variables, such as the presence of home literacy resources and materials for the development of home language, may better capture contributing factors to reading achievement growth for language minority children with limited English skills.

Classroom literacy practices and ESL program features. Analyses concerning research question three focused on how several ESL/bilingual program features and teacher variables might influence the reading progress of individual children during their early childhood years. A few findings are informative. First, although no consistent effects associated with ESL or bilingual programs were discerned across language backgrounds over the course of kindergarten and first grade school years, there was some evidence showing the benefits of bilingualism as early as kindergarten. Specifically, among Mixed Bilinguals, during kindergarten, EL students seemed to have a distinct advantage in reading growth compared with their non-EL peers. There was also some evidence regarding the positive impact of time allocated to ESL-related activities during kindergarten, indicating that EL students speaking both English and their home language fairly well seemed to benefit the most from participating in their school's ESL/bilingual program. It follows that language minority students with higher levels of bilingual proficiency are likely to experience the cognitive benefits as discussed by Bialystok (2001) and Cummins (2000), such as developing divergent thinking skills, metalinguistic skills, and displaying reading awareness earlier than monolingual students. Unexpectedly, no such positive associations of ESL programs were found during first grade, a finding noted in another study suggesting the issues concerning EL classification in some school districts (Bailey & Carroll, 2015). There is some evidence that districts who do not reclassify prior to third grade have lower overall rates of reclassification (Parrish et al., 2006), lending credence to concerns that ready-to-be classified students in early elementary grades may experience deleterious effects from remaining in Title III (EL) programming.

With respect to the specific type of ESL service identified students received, results were mixed for both LEPs and Mixed Bilinguals. Receiving in-class ESL services was positively associated with LEP students' reading growth but negatively associated with reading growth for English Monolinguals and Mixed Bilinguals. It could be that for students with relatively higher English proficiency, receiving ESL service within the classroom took away their time mastering the academic content, thereby impeding their reading progress. In contrast, students with limited English proficiency clearly benefitted from increased exposure to the English language input whether the program structure was in-class or pullout, with the latter proving to be more beneficial. Interestingly, having an available ESL aide service was a statistically significant program feature for EL students who reported speaking English only at home, as a moderate percentage of students within English Monolinguals were found to need English language service (i.e., 15%). Together, these sets of findings replicate exiting studies indicating the positive effects of bilingualism on academic achievement (Han, 2012), and further, they suggest the differential effectiveness of particular classroom language supports available varies for students with differing levels of English proficiency skills.

Furthermore, teachers' allocation of time to building key literacy skills, unexpectedly, exerted no statistically significant influence on English Bilingual or Mixed Bilingual students' reading growth during kindergarten or first grade, and notably, the coefficients, albeit statistically non-significant, were in the negative direction. In contrast, for English Monolinguals and for LEPs teachers' allocation of increased instructional time for building key literacy domains was positively related to reading growth. Moreover, the positive effects were found during both kindergarten and first grade for LEPs—a group of students with non-English dominant language background. These results may provide some initial evidence regarding the nuances in students' acquisition of English language skills among different language background groups. Notably, there were also considerable gaps in reading growth between EL and non-EL students within these two language background groups. In other words, there still remained a significant gap between ELs and non-ELs with respect to reading growth at these two critical junctures, given differences in teachers' responses regarding their classroom time allocated to targeted literacy skill developments. For first grade, however, EL students were significantly more likely to be assigned to teachers who did not spend as much time on the identified set of pre-reading and reading skills.

It is worth noting there was a shift in the mechanism concerning family SES, home literacy practices, and children's development of reading once they received formal schooling. Results suggested that experiences and resources associated with the school were understandably more associated with reading skills acquisition rates during kindergarten and first grade, particularly for Mixed Bilinguals and LEP children. Thus, there was an observed shift in the relative relationships of these settings once children entered school, such that qualities of classroom practices and school ESL program features were more associated with differences in reading achievement than family mediators were associated with such differences. Accordingly, family characteristics can be viewed as being strongly associated with the starting point of children's reading competence, with other ecological settings being stronger associated with subsequent children's reading progress. This underscores the important role schools play in leveling the academic playing field for children, especially those from socioeconomically disadvantaged backgrounds. This perspective is also supported by the work of earlier seasonal learning researchers who viewed schools as the "great equalizer" due to the more equal learning outcomes produced (Downey et al., 2004).

Interestingly, neither English bilinguals nor Mixed bilinguals in this study did not seem to benefit much from teachers' instruction on literacy skills either during kindergarten or first grade. This could be an indication of a lack of appropriate instructional practice for students who were in the process of developing bilingual proficiency. As recommended in the position statement from National Association for the Education of Young Children (2009), instructional strategies and practices need to speak to the social and cultural contexts of children with linguistic and culturally diverse backgrounds. Further, teachers need to understand the sequences in which a domain's specific concepts and skills are learned and have ready a well-developed repertoire of teaching strategies to employ for different purposes. The absence of measures assessing teaching quality precludes the initiatives to ruling out this alternative explanation. In contrast, students speaking predominantly English and home language seemed to benefit from instructional strategies focusing more on phonics, such as word decoding, sounding out letters, and phonemic awareness, providing some evidence of cross-language effects in the acquisition of English language skills (e.g., phonological and vocabulary development, see Genesee et al., 2006), given that the majority of students speaking limited English were of Hispanic origin.

These results, together, indicated students with differing language background and English proficiency skills had varied capacities in taking advantage of the available resources, and in a similar vein, programs designed to benefit EL or language minority learners need to consider the individual variation existing among students of diverse linguistic backgrounds in developing effective school programs. Future studies can incorporate measures assessing students' language and literacy skills in their home language because language development in the student's home language was found to facilitate the process of new language acquisition (see Baker, 2011; Genesee et al., 2006).

Identifying school variables contributing to reading growth of latent reading profile groups. Results from the last set of analyses revealed three emergent reading growth trajectories distributed across students with diverse language backgrounds. Specifically, there were disproportionate ELs in each latent class and, as expected, ELs were overrepresented in the low-achieving reading profile group. Further, controlling for family and classroom characteristics, membership in the low-achieving reading profile group was primarily affected by attending a school that had lower reported involvement in school academic improvement processes over time, a higher proportion of LEP students, and fewer years of ESL programs available for EL students. These results are consistent with a large number of existing studies decrying the overrepresentation of language minority students with limited English proficiency skills concentrated in schools with fewer resources (Han, 2012; Lee, 2010; Rumberger & Gándara, 2000). The findings of the present study, therefore, speak to the detrimental effects of grouping and segregating that occurs within schools, which indirectly, and considerably, impinged on students' reading achievement growth during kindergarten through third grade. This finding echoes García Coll et al.'s (1994) integrative model, which suggests that ethnic and language minority children's social position situates them in a learning environment that is fundamentally different from their mainstream mid- and upper-class English monolinguals, by which implicit barriers, such as limited education resources and language programs, are detriments to their achievement outcomes (García Coll et al., 1994; Garcia & Szalacha, 2004).

Notably, the results from the mixture analyses cross-validated the previous analyses from a different perspective, demonstrating the salience of language background in understanding the mechanisms underlying development of English language development concerning family characteristics and school contexts and processes. In addition, teacher experiences and preparation in coursework concerning early childhood and ESL students were examined, given schools with high concentrations of minority students and high concentrations of students from low-income families tend to have higher percentages of uncertified and novice teachers (Capps et al., 2005). Contrary to initial hypotheses, none was significant in predicting group membership or explaining students' reading growth, which is consistent with other work (e.g., Aikens & Barbarin, 2008; Xue & Meisels, 2004). Teachers' experience, preparation, and classroom literacy instruction were not consistently related to children's reading outcomes. However, previous findings examining teacher effects remain largely elusive (Early et al., 2006). One reason is that these differences are confounded with teaching quality. Another is the challenge of obtaining measures more up close to teachers' day-to-day instruction and strategies used as opposed to the yearly self-report measures available in these data. Further, there was no evidence suggesting the positive effects of ESL-related services, such as translators for parent-teacher conference and home visits, for students' reading growth *per se*, replicating Han's (2012) findings that such positive effects were beneficial for math growth but not for reading growth. These findings underscore the necessity of collecting more nuanced information regarding the quality of classroom instruction in order to explore more viable and effective teaching strategies for students of linguistically diverse backgrounds.

Limitations and Future Research

The results must be considered in terms of several limitations. First, the data collection utilized during the ECLS-K study only provided fall and spring assessments for children during kindergarten and first grade. After first grade, student assessments only took place during spring third grade, spring fifth grade, and spring eight grade. This assessment schedule was useful in observing overall student growth during a prolonged period but did not facilitate examining how classroom processes might support the reading progress of students past their initial two years in school. Unfortunately, only 30% of the original sample was sampled during fall of first grade (i.e., the third wave of data collection). Therefore, the appropriate longitudinal child weight for K-8 participation was constructed in ECLS-K on this relatively small subset of individual students who were followed continuously throughout all waves of data collection. In addition, students could not be matched to teachers during grades two through seven, making difficult to investigate how teaching practices and classroom features might contribute to reading growth (or prolonged reading difficulties) past first grade.

Second, while a variety of longitudinal weights were available for examining growth on the student level, it was impossible to examine the multilevel structure (i.e., students nested within classrooms and schools) on a year-to-year basis, especially about classrooms. In ECLS-K: 2011, this issue was properly addressed with consecutive data collection taking place twice a year (i.e., fall and spring) for each grade level until grade five (Tourangeau et al., 2015). In addition, classroom information was also included in the teacher-level questionnaire regarding use of class time, instructional activities, curricular focus, and other aspects of classroom. This allows the researchers to link the student data with teacher-level data seamlessly in order to further examine the effects associated with classroom practices and teaching strategies. Note that whether children had changed teachers between rounds of data collection was also specified.

Third, in some cases, it was challenging to define constructs optimally. One example was in defining home literacy environment due to changes in items over rounds of parent data collection and as students got older, there was a lack of items specifically addressing how parent practices might change. In addition, home literacy environment was constructed as a composite variable in the study; yet, future research can consider utilizing latent transition analysis that uses time-specific latent class variables measured by multiple indicators (i.e., items defining home literacy practice) at each time point to study changes in class membership over time (Muthén, 2004). In a related vein, family SES could be conceptualized as a dynamic measure at different time points as the life-course theory suggests the value of examining how various aspects of SES, singly and in combination across time, affect patterns of development (Bornstein & Bradley, 2003).

Fourth, as most research in dual language acquisition pointed out, lack of data on children's home language skills and knowledge is a major shortcoming in most datasets (e.g., see Gutiérrez et al., 2010). ECLS-K is no exception in this case; thereby precluding me from examining children's first-language practices and experiences with literacy. There is mounting evidence suggesting that children learning two languages will use information from their first language to build their understanding of how language functions in their second language and vice versa (e.g., Dickinson, McCabe, Clark-Chiarelli, & Wolf, 2004; Howard et al., 2014). Thus, oral language development in the home language has important implications for understanding the general cognitive functioning of young children speaking another language other than English as well as how it facilitates their English language acquisition process. Related to this, the challenge of operationalizing language background or experience needs to be addressed adequately, both conceptually and empirically with other data if possible, that is, with more robust measures of quantity and quality of language input in both languages, as well as language proficiency such as children's mean length of utterances in each language.

Last, LEPs did not include students who were disqualified from taking the tests during early waves of assessments. This may have resulted in some systematic bias based on the exclusion of students who were slowest to acquire English proficiency and therefore were likely to have low reading achievement scores. As Xue et al (2006) found, students who were excluded from taking the screening test were more likely to be of Hispanic origins, come from low-income homes, and speak limited English. In this study, although about 70% of the LEP group had missing reading assessments at kindergarten entry, mainly due to the English language screener, nearly 73% had reading scores by the first-grade year.

Conclusions and Future Directions

The study provides an alternative way of conceptualizing the heterogeneity issue germane to the language minority student population with the aid of the latent growth analysis framework. It can be considered as an initial attempt applying GMM to address issues of growth patterns and latent class membership, which has only been seldom attempted in the prior research on reading development (e.g., see Cheng & Al Otaiba, 2013; Liu et al., 2016). Notwithstanding the constraints of self-report measures, the study made use of the available information to construct a variable indicating children's diverse English language proficiency—language background—and included it in the latent curve analysis to examine its moderating effect on the proposed relationships. Further, school-designated status, as collected from school administrators in the ECLS-K at the onset of the study, was incorporated as a covariate to investigate its effect on predicting latent reading growth trajectories. To a large extent, results of the two approaches, via both known and unknown groups, were consistent. Thus, the current study make a contribution to the literature by focusing on reading development during an extended period of time (i.e., kindergarten through eighth grade), by utilizing latent growth mixture models, and by relying on both home language background and school-based EL status to identify students belonging to each language profile group.

The results of the study advance the discussion of reading growth for language minority students in at least two ways. First, the picture of EL students' reading growth trajectories is more layered and complex when unpacking language minority status by examining children's individual language background as a more detailed way to capture their English language proficiency skills. EL students were actually spread out across language backgrounds, and their "response" and achievement with respect to the services they received in their classrooms and schools can be differentially effective, resulting from their unique language needs derived from their home language usage. Second, the study integrated a known-groups analytic approach to consider the different reading skill profiles due to language background and then cross-validated these findings regarding EL status and achievement with a second approach that identified three emergent groups separated by EL status, as well as a set of classroom and school predictors that indirectly affected growth in reading over time as a result of their influence on the membership of the latent trajectory classes. These results form a different prism through which school contexts and processes can be examined with respect to their mediating role in shaping the reading profile groups as well as their direct effects on students' reading growth during early reading development.

These findings highlight several important areas for future research. First, research is needed to understand the growth trajectories of children of diverse linguistic backgrounds in greater detail, using more advanced statistical methods such as GMM. Second, future research should examine how specific classroom practices and teaching strategies influence the growth trajectories of the three reading profile groups, especially for the bilingual students. As research concerning teacher effects, especially for development of reading, remains inconclusive, further deliberations and considerations are needed to capture classroom dynamics with regard to teaching quality and developmentally and culturally appropriate practices for linguistically diverse students. Additionally, further analyses can help clarify the different aspects of school resources focusing on improving EL and language minority students' English proficiency and academic content. Importantly, in the current study, ESL program features were confined to either pullout or in-classroom, which may not apply to some school districts where both were integrated into children's ESL program routine. Additionally, with the implementation of the Every Student Succeeds Act (2015), school districts are held accountable for appropriately identifying English language learners as well as reclassifying them as they begin to demonstrate adequate English proficiency. Hence, future research should incorporate broader assessment measures for English proficiency and further examine the relationship between English academic proficiency and academic content mastery, such as reading comprehension.

Broader Implications

The findings of this study have important implications for educators, teachers, and policymakers in the broader context of early childhood and early elementary education. First, and foremost, given the changing demographics of English language learners and language minority students (or dual language learners), teachers, educators, and policymakers should not treat language minority students or EL students as a homogenous group. Instead, understanding that language minority students constitute considerable heterogeneous demographic patterns can help address the learning needs of children of diverse language backgrounds. Second, school personnel need to differentiate the type of English language programs and services for students with differing English proficiency skills, especially for subgroups of children from socioeconomically disadvantaged background. In particular, school districts need to have more refined measures for identifying and reclassifying EL students to reduce the negative stereotypes induced by language minority status. In addition, school districts should collect data by ethnic and language subgroups as opposed to EL status alone. Third, with regard to teaching strategies, teachers need to respond to each child's individual characteristics and integrate language minority children's linguistic repertoire into instructional practices. By attending to the multiple domains of development, such as issues relating to bilingual development, educators and professionals in early childhood and elementary education can employ developmentally appropriate practices that can effectively promote each child's development of reading and learning.

Appendix A. Reading Growth Effect Size across Language Background Groups

	EB-EM	MB-EM	LEP-EM	MB-EB	LEP-EB	LEP-MB
Fall K (entry)	0.16	-0.46	-0.83	-0.63	0.99	0.83
Kindergarten	-0.07	0.26	-0.17	0.33	-0.10	-0.43
First Grade	-0.03	-0.04	0.21	-0.01	0.22	0.25

Notes. EM represents English Monolinguals, EB represents English Bilinguals, MB represents Mixed Bilinguals, and LEP represents Limited English Proficient.

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